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A 2-PHASE ASPIRATION-LEVEL AND UTILITY THEORY APPROACH TO LARGE SCALE DESIGN

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ABSTRACT

The ability to make rational decisions is one of mankind's unique attributes. A characteristic of the formal techniques that have been used for decision making is the selection of the best alternative with respect to a certain figure of merit. One of the most critical problems in engineering design is making early decisions on a sound basis. However, the early stages of design are also the most uncertain, and obtaining precise information upon which to base design decisions is usually impossible. The need for a methodology to represent and manipulate imprecision is greatest in the early, preliminary stages of engineering design, where the designer is most unsure of the final dimensions and shape, material properties, and performance of the completed design. Utility Theory provides an analytical way to aid the decisions in engineering design. By exchanging from objective to attribute and expressing these attitudes mathematically, a utility based attribute function (Utility Function) can be set up to describe the attitude of a decision-maker with regard to his/her preference. In this work, the Aspiration-level Interactive Method (AIM), a goal-seeking method based on identifying non-dominated solutions, is used along with Utility Theory to compensate for the limitations of utility theory in forming a meaningful group preference. This work is an initial attempt to integrate two methodologies from the field of decision theory in order to provide rational decision support for design problems where a hierarchy of decision making is required. The hierarchy, in this paper, is characterized by multiple designers at the lower level who report to one manager. The designers each have different preferences and values, while the manager is driven by project goals and specifications. The approach presented generates feasible and preferred design combinations for further analysis in the detailed design phase.

NOMENCLATURE

SUF: Single-Attribute Utility Function
MUF: Multi-Attribute Utility Function
AIM: Aspiration-level Interactive Method

1 INTRODUCTION

Keeney defines decision analysis as a "formalization of common sense for decision problems which are too complex for informal use of common sense." (Keeney and Raiffa, 1976) The primary purpose of decision analysis is to evaluate alternatives and guide the decision-maker. Keeney discussed the methodology of decision analysis in four main steps (see Figure 1):

1. Structure the decision problem (define objectives and attributes),
2. Assess possible impacts of each alternative,
3. Determine and quantify preferences (values) of decision makers, and
4. Evaluate and compare alternatives

In assessing the possible impacts of each alternative in Step 2 many external factors must be accounted for. During uncertain situations, these external factors are both beyond the control of the decision-maker or unknown to the decision-maker at the time of the decision. Each configuration of external factors represents a possible situation for the decision-maker. These configurations are the states of nature for the decision problem (French, 1986). These consequences are not always known in advance to the decision-maker.

The field of decision making is commonly classified to whether a decision is made by an individual or a group under the situations or conditions of certainty, risk and uncertainty

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(Luce and Raiffa, 1957). Decision making under certainty deals with problems which can be solved in an environment where the decision-maker deals with only one state of nature.

Decision making under risk constitutes the condition where there is information unavailable, but a probabilistic description of the missing information is available. Decision making under risk deals with true states of nature, which is often unknown to the decision-maker. Since the decision maker does not know the true states of nature, he may subjectively quantify his uncertainty using a probability distribution over all possible states of nature. Decision making under uncertainty, by contrast, involves distributions that are unknown. This situation involves less knowledge than decision making under risk.

One of the most critical problems in engineering design is making early decisions on a sound basis. However, the early stages of design are also the most uncertain, and obtaining precise information upon which to base design decisions is usually impossible. The primary reason for the difficulty is that imprecision is an integral part of the engineering process - not imprecision in thought or logic, but rather the intrinsic vagueness of a preliminary, incomplete design description. At the concept stage, the design description is nearly completely vague or imprecise. The design process reduces this imprecision until ultimately the final design description is precise. The need for a methodology to represent and manipulate imprecision is greatest in the early, preliminary stages of engineering design, where the designer is most unsure of the final dimensions and shape, materials and properties and performance of the completed design.

There are a number of methods to handle risk and uncertainty in design decisions. In this paper, we develop a method for decision making under risk for problems where there is a hierarchy of decision makers, as shown in Figure 1. At the lower level, the designers are entrenched in the technical and economic details of the design, while at the upper level, the manager is commissioned with meeting requirements and setting goals for the project. We adopt a "benevolent dictator" approach as provided by Keeney and Raiffa (1976) where a top-level decision maker makes the final choice after considering other group member preferences.

The approach aggregates the highly preferred design alternatives from each design team member into a final set that the manager can focus their attention on in subsequent stages of the design process. The first stage of the process analyzes the design alternatives against each individual designer's preference structure, and constructs a set of highly suggested designs. In the second phase of the process, the top-level decision-maker manipulates this suggested design set by specifying aspiration levels on each design criteria. The extent to which the suggested designs satisfy these aspiration levels, determines the final design alternative set. The approach and the fundamental assumptions it is built upon are given in Section 3, following Section 2 where the engineering

design work relevant to the developments of this paper is presented.

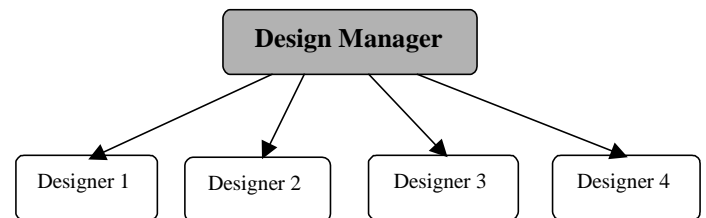


Figure 1. Designers – Manager Decision Hierarchy

2 BACKGROUND

In this section, previous work in modeling design decisions under risk is reviewed. Also, limitations of previous methods are discussed. The fundamentals of the methods used in this work are also presented.

2.1 Previous Work

Keeney and Raiffa (1976) present classical utility theory and its related axioms. Their work comprises the foundation upon which all subsequent utility theory applications are built. Concepts including multiple criteria decision making under certainty, uncertainty and risk are all outlined and addressed.

In (Thurston, 1991; Thurston, 1994) design measurement is based on multi-attribute utility theory, which allows the designer to emphasize preferences in certain attributes. These preferences then help in the construction of a design evaluation equation that can then be used to determine the net change as the levels of the individual attributes change. Utility theory helps the decision maker to choose between accepting a single alternative or a lottery with certain chances of outcomes which may be better or worse. This determines and represents the willingness of the decision maker to make tradeoffs between attributes.

Hazlerigg (1996) also explains the use of utility theory extended to the von Neumann-Morgenstern lottery in making a choice among a given certain number of design options. When perfect information is available a simple lottery can be constructed and in the case of imperfect information we can have a choice between a simple or compound lottery based on our decision to conduct an experiment. The experiment, which is conducted in the case of a compound lottery, results in outcomes each occurring with certain probability. Then, based on the outcome of the experiment, a second lottery is entered. With the various outcomes obtained, a choice can then be made.

The Analytic Hierarchy Process (AHP) has been widely used as a decision making tool for complex, multi-criteria problems where both qualitative and quantitative aspects of a problem need to be incorporated (Saaty, 1994). However, Barzilai (1998) questions the accuracy of the AHP and demonstrates how the results from using AHP can be illogical and meaningless.

While utility theory and AHP are generally accepted to be value-oriented approaches (a decision-maker states

preferences between criteria or alternatives), in (Kersten, 1985) a goal-oriented approach, where a decision-maker explicitly states levels of criteria attainment that are required or desired, is proposed. Because utility functions are non-stationary, group interactions will cause change in individual utilities, and therefore group utilities. In a situation where group members have conflicting objectives, conditioned compromises are likely to appear, with participants willing to accept settlements only when others make concessions. This may lead to a situation where group members refuse to accept solutions where only some, but not all, members' positions are improved and the group may then end up selecting a dominated solution. Therefore, the suggestion in (Kersten, 1985) is to use an aspiration-level based, or goal-oriented approach, where aspiration levels are set for each goal or attribute and used to identify the best alternative.

Tietz and Bartos (1983) conclusions support the use of aspiration levels. The results of their analysis were that aspiration levels better explained negotiation outcomes than utility approaches. They believe that aspiration-based schemes allowed decision makers to modify their preferences more easily during the decision-making process, and aspiration levels were more readily used by decision makers to summarize the learning that occurs during the decision making process. During the process of seeking solutions with specific attainment levels, group members could see the tradeoffs more clearly.

In (Zionts, 1992) a method called the Aspiration-level Interactive Method (AIM) is presented. This method provides the decision maker with aspiration-levels, or 'bands of satisfaction', for each discrete design configuration to fall within, based on prescribed preferences. It is a decision tool designed to assist a user in exploring decision alternatives in a user-driven manner, generating non-dominated solutions that are close to the user's levels of aspiration. It includes concepts based on goal programming and other aspects of Multi-Criteria Decision Making (MCDM). Also, using a Tchebycheff approach (Chen, 1999), the "nearest non-dominated solution" alternatives are defined and presented to the decision-maker.

2.2 Limitations

Most design decisions involve a desire to fulfill multiple objectives. To deal with such situations the concepts of multi-attribute decision making have been contrived. However, a difficulty with multi-attribute methods is the absence of any objective model capable of dealing with many criteria. Limitations and weaknesses of the methods briefly described in the previous section are examined a little further.

Utility analysis enables the designer to think in terms of function rather than form, freeing the designer from cognitive biases. However, utility analysis does not contribute much to the creative or configuration phase of design, except to help identify which attributes are worthy of focused attention. Utility analysis cannot be the only analytic tool employed in design. It cannot tell the designer which raw material options

are available, or the beam cross section required to sustain a particular load (Thurston, 1999).

Another important limitation is the approach to aggregating individual preferences into a group preference. Design is most often a team effort, requiring specialists in materials, structures, manufacturing, etc. Again, specialists employ their knowledge to develop a configuration that optimizes the objective(s) relevant to them. The problem then becomes the group decision problem: how to identify the design that is best for a group as a whole? Balancing tradeoffs between objectives is even more important in-groups than for individuals, because conflicting objectives and opposing viewpoints are inevitably going to exist.

A major problem in supporting group decisions is the aggregation of group preference. In the field of utility theory, Keeney and Raiffa (1976) provide conditions for the existence of a group's cardinal choice function. Keeney and Raiffa adopt a "benevolent dictator" approach where a top-level decision maker makes the final choice after considering other group member preferences. However, real world implementation of this approach is not easy, as an unexpected difficulty is that group members may disagree about the benevolent dictator's choice.

Four common limitations to group decision making (Ngwenyama, 1999) are:

1. Inability to deal with vagueness of human decision makers in articulating their preferences.
2. Difficulty in mapping qualitative evaluation into numeric estimates.
3. Problems aggregating individual preferences into meaningful group preference.
4. Lack of simple user-friendly techniques for dealing with a large number of decision alternatives.

Utility theory does not resolve these central problems of group decision making. However, team design decisions must be made and utility analysis provides an organized, structured framework that decomposes the problem into smaller decision problems (Thurston, 1994).

In this work, we integrate Utility Theory and the Aspiration-level Interaction Method in order to compensate for the limitations of each method in order to provide a more comprehensive approach to rational decision making in a hierarchical environment, as shown in Figure 1. Utility Theory is utilized at the lower level (designer level) in order to facilitate rational decisions of each designer. We then utilize AIM at the upper level (manager level) to find non-dominated solutions from a goal aspiration approach. The next section describes the fundamentals behind each of these methods.

2.3 Utility Theory

Utility theory is a method used in decision analysis in engineering design. This method first models the decision situation by mapping the design option space to the performance attribute space, and then obtains the designer's preference information regarding the tradeoffs among the attributes. A system utility function on the attributes is then

constructed to represent the overall desirability of any combination of attributes.

There are three basic risk attitudes towards one attribute: Risk Averse, Risk Prone and Risk Neutral, which illustrate the degree of the decision-maker's confidence in being successful. Two possible conditions exist: monotonic increase (the more the better) and monotonic decrease (the less the better) which reflect utility change trend with the attribute increase. For convenience, it is common to set the most preferred attribute level with utility "1" and least with "0".

A function f is called monotone on (a, b) if it is either always monotone increasing or monotone decreasing. A sequence $\{a_j\}_{j=1}^{\infty}$ is called monotone increasing if $a_{j+1} \geq a_j$ for all j , and monotone decreasing if $a_j \geq a_{j+1}$. Unless dealing with deviation values, strict monotonicity is a very reasonable characteristic for a utility function in engineering design, as engineering design objectives generally seek to minimize or maximize objective function values (e.g., the lower the cost the better, the lower the stress the better, or the higher the reliability the better).

Utility Theory was originally designed for management decisions, not for engineering design, and requires that all attributes be aggregated into a single goal. Economists generally believe every aspect of a decision can always be translated into a monetary cost, where monetary costs are additive. Aspects which are not additive, or which cannot be 'bought off', are not deemed possible. The axiom of Utility Theory, which creates the demand that a gain in any aspect must be able to compensate for any loss in any other aspect, is the Archimedean property (Keeney & Raiffa, 1976).

This restriction requires that any decrease in overall preference caused by changes in the performance of one variable must always be able to be balanced by an increase in performance in any other of the variables. Clearly this is not the case in engineering design. For example, given a fixed material, the tensile strength limits cannot be exceeded no matter what the reduction in the design's costs. Material stress simply cannot always be traded-off in a compensating fashion. This implies Utility Theory will not permit a worst case analysis, which is required in many instances in engineering design (Thurston, 1999). This limitation is addressed in this work by applying the constraints and restrictions at the beginning of the analysis while the alternative list is first constructed.

We utilize Utility Theory and its associate lotteries at the lower-level decision problem. Namely, we utilize the mid-level splitting lottery to assess a decision maker's SUF and a multiple attribute lottery to assess a decision maker's MUF. These lotteries are illustrated in Section 4. We aggregate the preferred alternatives from each designer (as predicted by their multiattribute utility functions) and then utilize the Aspiration-Level Interactive Method (AIM) to facilitate the upper-level decision problem of selecting from among these preferred

designs. The Aspiration-Level Interactive Method is described in the next section.

2.4 Aspiration-Level Interactive Method

The Aspiration-Level Interactive Method (AIM) is a decision tool designed to assist a user in exploring the decision alternatives in a user driven manner, generating non-dominated solutions that are close in some sense to the user's level of satisfaction (Zionts, 1992). One solution dominates another if the first solution is at least as good in every criterion and strictly better in at least one of them. Solutions that are not dominated by any other solutions are called non-dominated solutions. The user adjusts the level of aspiration for each objective while obtaining feedback on their reasonableness. AIM then provides the closest non-dominated solution to the aspiration levels.

Every objective is assumed to be either a maximizing or minimizing objective. More formally:

T_i = represent the satisfying threshold for objective i

z_i^k = be the value of alternative k in terms of objective i

A_i = be an aspiration level for objective i , which should not, in order to be meaningful, exceed the ideal value for a maximizing objective, and vice versa.

Further, we define the ideal (I_i) and nadir (N_i) values for objective i as (Zionts, 1992):

$$I_i = \begin{cases} \min [T_i, \max_k \{z_i^k\}] & \text{if } i \text{ is maximizing} \\ \max [T_i, \min_k \{z_i^k\}] & \text{if } i \text{ is minimizing} \end{cases}$$

$$N_i = \begin{cases} \min_k \{z_i^k\} & \text{if } i \text{ is maximizing} \\ \max_k \{z_i^k\} & \text{if } i \text{ is minimizing} \end{cases}$$

In a maximization case, the ideal and nadir points provide upper and lower bounds on A_i . The z_i^k values are ordered from the least to most preferred, for each objective i . The decision-maker is provided with the following set of 'basic information' (Zionts, 1992):

- (a) A_i , the current goal for objective i , initially set to the median, together with the proportion of alternatives that are at least as good as this value.
- (b) Two other aspiration levels; the next better, and next worse, levels than A_i .
- (c) The ideal (best) and nadir (worst) values for each objective.
- (d) The proportion of alternatives that simultaneously satisfy the given aspiration levels.
- (e) A "nearest non-dominated solution".

The ideal and nadir solutions are the names given to the fictitious solutions that achieves all best and worst values respectively. If the ideal solution were not fictitious, it would dominate all other solutions, and it would obviously be chosen.

The next section describes the overall method proposed in this paper to address the difficulties of decision making during the early stages of design. It combines concepts from Utility Theory and the Aspiration-Level Interactive Method.

3 PROPOSED METHOD

The approach described in this paper combines Utility Theory and the Aspiration-level interactive method in a 2-phase manner as shown in Figure 2.

Initially, the alternative and attribute spaces are generated. The alternative space is the complete set of solutions to be evaluated by the decision-maker, the attribute space comprises the set of criteria upon which each alternative will be evaluated. The assumption in this work is that these spaces exist. During this preliminary stage it is also implied that the system-level decision-maker decides the composition of his design; i.e.: number of team members and the areas of expertise each represents.

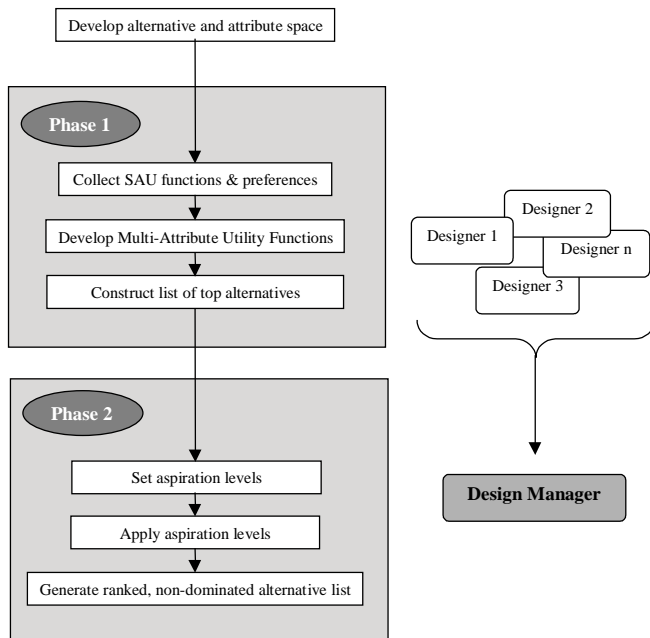


Figure 2. 2-Phase Method

The first step of Phase 1 is the collection of Single Attribute Utility Functions (SAUFs) from each of the lower-level design decision-makers on each of the design attributes. The necessary SAUF assessment steps are described in detail in (Callaghan, 1999). Basically, a set of lotteries are proposed to the designer with the intent of capturing their preferred range, and acceptability of values on each individual attribute, independent of the others.

Once completed, the second step is to develop Multi-attribute Utility Functions (MAUFs) for each of the lower-level designers by using a different type of lottery where attributes are combined into a tradeoff procedure. Each alternative is then evaluated on the basis of the preferences of the decision-makers as represented in the MAUF, and is subsequently given

a utility score, and ordinal ranking based on the utility score. A number of top ranked alternatives from each decision-maker are merged together to construct a list of highly suggested alternatives to be passed into the next phase and onto the top-level decision maker (Design Manager in Figure 2). In the study of this paper, the top 50 alternatives were selected and passed onto Phase 2. The size of this list is problem specific and determined by the top-level decision-maker.

In Phase 2, the top-level decision-maker sets attribute aspiration-levels, or minimum levels of performance, required of the alternatives. Our assumption is that the top-level decision maker remains benevolent and rational (Keeney and Raiffa, 1976) and therefore uses the preferred designs given to him by the designers. Application of these aspiration levels to the set of suggested alternatives from Phase 1 generates a ranked, non-dominated alternative list. This final alternative list contains the design alternatives considered worthy of further analysis in latter stages of the design process as indicated by the aspirations of the system-level designer and the preferences of the members of the design team.

Theoretical Implications of Approach

Our 2-phase approach rests on the assumption that the top level decision maker is indeed benevolent or rational in the sense that they manipulate the set of alternatives provided to them by the lower level designers and not another set of alternatives (Keeney and Raiffa, 1976). The validity of this assumption rests on the premise that the lower level designers are providing quality and rational designs to the upper level decision maker. We utilize utility theory to insure this lower level rationality.

Integration of two methodologies, while possibly capitalizing on the advantages of each method, could also share the flaws in each methodologies. While we feel like we are able to capitalize on the strengths of both methods, more work is required in order to thoroughly investigate the theoretical implications of our integration. This paper represents an initial attempt to integrate two valuable and complementary decision making methodologies in order to provide decision makers more rational support in the design of large-scale systems in a hierarchical decision making environment.

Coupled together, these two methods provide the top-level decision-maker with a technique to evaluate design alternatives suggested to him by the lower-level designers (could be comprised of engineers, managers, or other personnel). If working alone, Phase 2 is not enough because it assumes a large percentage of design knowledge to be in the possession of the top-level decision-maker. This is not usually the case, as this position is typically held by management, or individuals more interested in the 'larger picture' and not the specific needs of each sub-component. It would ignore the varying preferences and values of decision makers – a critical component when making decisions under risk and uncertainty.

Moreover, Phase 1 by itself, though sufficient for individual preference, or single subsystem analysis, is

inadequate for specifying a group preference and establishing goal aspiration targets.

The proposed method is now applied to a case study concerning the design of a passenger aircraft.

4 CASE STUDY: DESIGN OF A PASSENGER AIRCRAFT

The following problem has been adopted from a rule based design problem developed by James L. Rogers, and can be found at the NASA-Langley MDO test suite [<http://fmad-www.larc.nasa.gov/mdob/MDOB/mdo.test/index.html>]. It has been slightly modified from its original format to suit the purposes of this analysis. To allow for more solution flexibility, the constraints of the originally posed design challenge have been converted to objectives, or criteria on which the different design configurations are evaluated.

Design Challenge: Within certain constraints, design the least expensive airplane while:

- Minimizing cost
- Minimizing weight
- Maximizing passenger capacity
- Maximizing range
- Maximizing speed (*Note: Mach is about 738 miles per hour.*)

Where:

$$TotalCost = \left(EngineCost * \frac{\#Engines}{Wing} * 2 \right) + FuselageCost + (WingCost * 2)$$

$$Total\ Weight = Total\ Engine\ Weight + Fuselage\ Weight + Total\ Wing\ Weight + Fuel\ Weight$$

$$Speed = Mach\ rating * 738mph$$

The aircraft is broken up into 3 main subsystems: the engine, fuselage and wing. Each subsystem has four characteristics, as shown in Table 1.

Engine	Fuselage	Wing
Weight per engine	Fuselage Weight	Weight per wing
Cost per engine	Cost	Cost per wing
Speed (mach #)	# Passengers	# lbs. of Fuel
Fuel consumption	Range	# Engines per Wing

Table 1: Airplane characteristics

There are five possibilities for each of the different subsystems. The specifics for the five engines, fuselages, and wings are listed in Tables 2 through 4, respectively.

Using the different component specifics listed in Tables 2 through 4, a total of 125 possible airplane configurations exist for the decision-maker to choose from. The next section provides a step by step description of the preference assessment and aggregation process.

	E 1	E 2	E 3	E 4	E 5
Engine Weight [lbs.]	11,000	12,000	4,000	13,000	5,000
Engine Cost [\$ Millions]	5.0	4.5	1.5	3.5	1.0
Speed [mach]	0.4	0.3	0.2	0.35	0.1
Fuel consumption [lb./hr]	200	100	50	150	20

Table 2: Engine specifics

	F 1	F 2	F 3	F 4	F 5
Fuselage Weight [lbs.]	55,000	36,000	20,000	25,000	11,000
Fuselage Cost [\$ Millions]	6.0	4.5	2.5	4.0	1.5
# passengers	400	300	350	200	100
Range [miles]	4000	2600	1200	3000	1000

Table 3: Fuselage specifics

	W 1	W 2	W 3	W 4	W 5
Wing Weight [lbs.]	25,000	20,000	15,000	10,000	5,000
Wing Cost [\$ Millions]	2.5	2.0	1.5	1.0	0.5
#lbs. fuel/ wing [lbs.]	2,500	2000	1500	1000	500
# engines/wing	2	1	1	2	2

Table 4: Wing specifics

PHASE 1: Assessment and Aggregation Process

The first step in the assessment process is the identification of the members of the design team, and the overall top-level design decision-maker responsible for the selection of the final set of preferred design alternatives. The six design team members and one system level designer were chosen from students and faculty with mechanical engineering or business backgrounds at the University at Buffalo (graduate students and faculty from the Department of Mechanical Engineering and School of Management). Each were interviewed separately and offered a brief description of the overall objective of the design problem and their general role as a member of the design team.

The next step in the assessment process is the decomposition of the design problem into the criteria up on which each alternative will be evaluated. Also involved in this step is specifying the desired direction of improvement on each criteria. In this case study, Cost and Weight are both to be minimized as Range, Speed and Passenger Capacity are to be maximized. Roger's airplane design problem is decomposed for evaluation in the manner depicted in Figure 3.

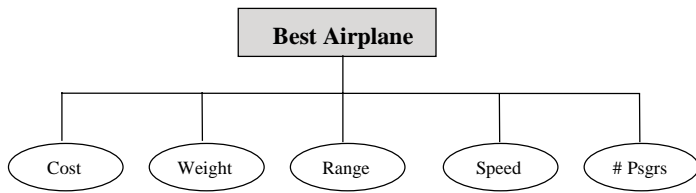


Figure 3: Airplane Design Decomposition

In this case study, the airplane is evaluated on the basis of five criteria: Cost, Weight, Speed, Range, and Passenger capacity. The relative importances of each criterion listed in Figure 3 vary across the different decision-makers, and are not yet known at this point.

The next step in the process is to convert each measure to a common metric. In the case of a utility analysis this common metric is ‘utiles’. The mid-level splitting method was employed at this stage to perform the conversion (Smith, 1999; French, 1986), as shown in Figure 4.

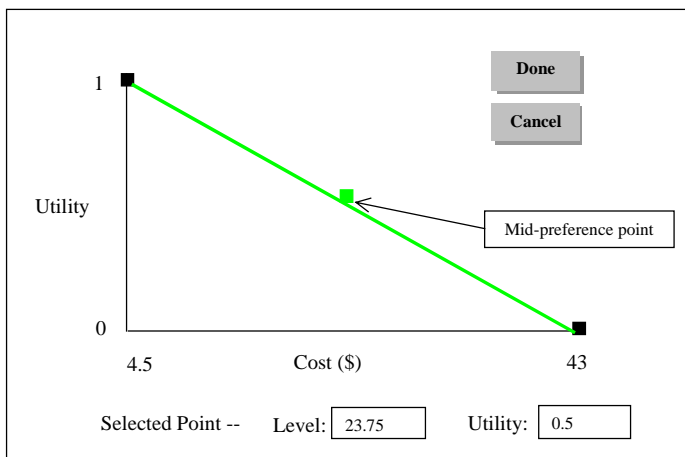


Figure 4. Example Utility Function Lottery Question

In the mid-level splitting assessment process the decision-maker is asked which range of change is more preferred, or significant to the decision-maker. The question accompanying Figure 4 would resemble: “Which change/range is more significant: ‘Change A’: 4.5 Million to 23.75 Million or ‘Change B’: 23.75 Million to 43 Million?” Supposing the decision-maker chose ‘Change B’ to be more preferred a change, the question continues with the following: “Between ‘Change A’: 4.5 million to 30 million and ‘Change B’: 30 million to 43 million, which do you now prefer?” If at this point the decision-maker finds that they are now indifferent between both Changes A and B, the midpoint (30 million) has been identified and is assigned a utility of 0.5. This utility, along with 4.5 million, (assigned a utility of 1 since it is most preferred) and 43 million (assigned a utility of 0 since it is least preferred) are combined to define the single measure utility function (SUF).

This iterative process is an essential step unless the decision-maker can initially specify at which point they are

indifferent between ranges of change. If at the beginning of the assessment they can specify their mid-preference point, this point is assigned a utility of 0.5, and a new criterion can be assessed.

Another variation of this method, occasionally applied at this stage, accommodates decision-makers not capable of expressing preferences over ranges of change. This second technique asks the decision-maker if each increment of improvement on the criterion is equally valuable. If so, the SUF remains linear, as seen in Figure 4. If not, the decision-maker is asked: “At which value are you indifferent to improvement on this particular criteria?”

Decision-maker 1 in Figure 5 expresses least preference for cost ranging from approximately 30 million to 43 million, and all values in this range are assigned a utility of 0. Decision-maker 2 in Figure 5 also assigns zero preference for designs costing in excess of 30 million, but states an additional preference that designs ranging in cost from 4.5 million to approximately 13 million are all equally most preferred, and assigned a utility of 1. These differences in preference are captured in the SUFs of each decision-maker.

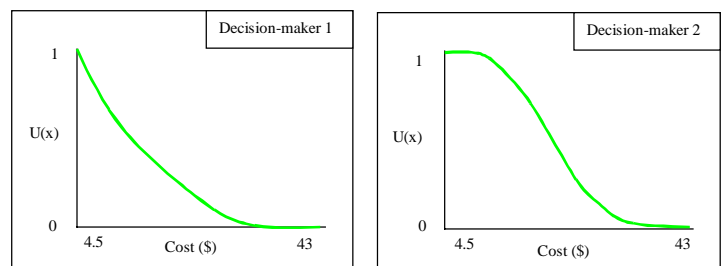


Figure 5. Example of Two Decision Makers’ Utility Function (SUF)

Once SUFs have been assessed over all criteria, the next step is to combine these SUFs into a Multi-Attribute Utility function (MUF). To accomplish this, an assessment regarding tradeoffs that the decision-maker is willing to make between hypothetical design alternatives must be conducted.

Figure 6 shows a sample tradeoff assessment question where the decision-maker is asked to choose between two designs: Alternative A (most preferred cost, least preferred weight) or Alternative B (most preferred weight, least preferred cost), or the decision-maker can express indifference between the two alternatives.

In the case of the decision-maker deciding Alternative B to be more preferred (cost more important than weight), the decision-maker is then asked to improve the value of A until it is equally preferred to Alternative B. This process determines the relative importance of criteria, and is reflected as weights in the MUF. This process is repeated until relationships are established between all evaluation criteria.

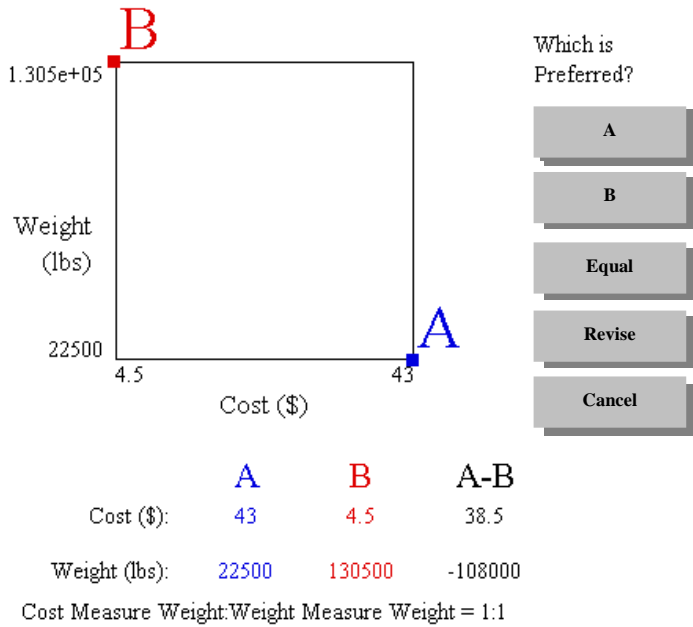


Figure 6. Example Lottery Question for MUF

At this point the criteria have all been converted to a common metric (utils), and the relative importance between criteria have been established, therefore, the utility functions for each criteria are fully defined. This process is repeated for all members of the design decision-makers team. These utility functions are used to determine the preferred ranking of design alternatives on each decision-maker. The next discussion presents the resulting rankings.

PHASE 1: Results

Figure 7 shows the preference profiles plot for the “passenger capacity” criterion. It is important to note that since these curves are based on preferences, there is no correct shape or form for the preference curve.

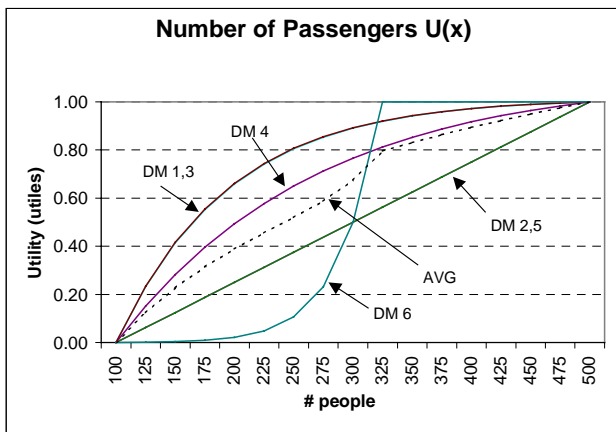


Figure 7. Utility Function Plots for Passenger Capacity Criterion

The dashed curve (AVG) is the utility trend for the group on that particular criterion. The majority of the curves shown in Figure 7 are exponential and exhibit risk averse behavior on the part of the decision maker, as indicated by their concave shape. Decision-maker #6 exhibits much different preferences for passenger capacity than the remainder of the group. Capacities of 150 passengers or less are all least preferred and assigned a utility of 0, and capacities of 300 or more passengers are assigned a utility of 1, most highly preferred. Preference profile plots for the remainder of the evaluation criteria are provided in Figure 8 (DM = Decision Maker).

Examining the “cost” utility plot of Figure 8, it can be seen that decision-maker #5 expresses linear preference for cost, meaning that each incremental reduction in cost is worth an equal increase in utility, hence the linear preference profile. In contrast, decision-maker #6 expresses high preference for costs including and under approximately 11 million, and least preference for design costs exceeding 38 million.

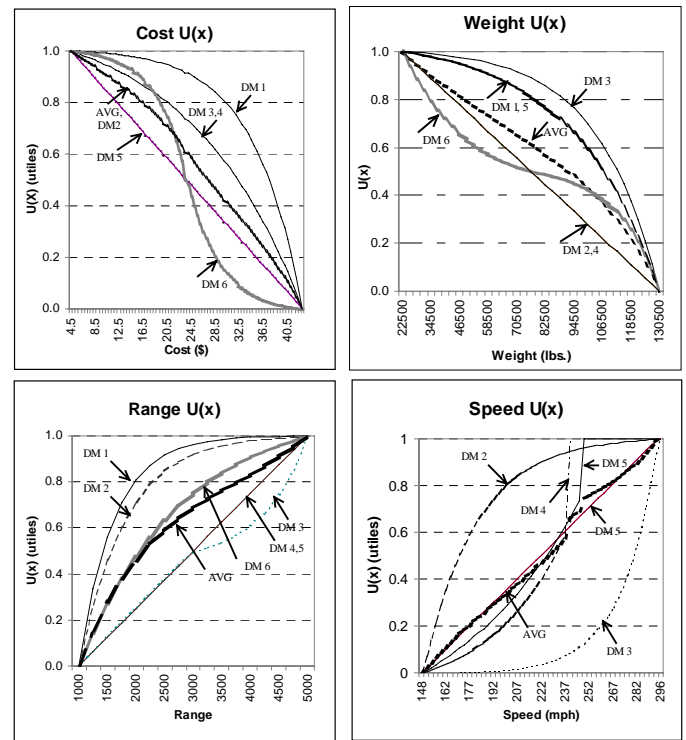


Figure 8: Preference Profile Plots for Cost, Weight, Range, Speed

Examining the “weight” utility plot of Figure 8, it can be seen that decision-makers #2 and #4 expresses linear preference for reduction in weight, in other words, every additional incremental reduction in weight is equally as preferred as the previous incremental reduction. Decision-maker #3 expresses high preference scores for weight values of approximately 46,500 lbs. and below.

Widely varying preference are expressed on the “speed” criterion. Decision-maker #3 expresses low preference for aircraft speeds from 148 mph up until approximately 200 mph.

Decision-maker #5 expresses linear preference for the speed criterion. Decision-maker #4 expresses high preference for aircraft speeds including and exceeding 240 mph.

Preference assessments for each of the six different decision-makers resulted in the criteria percentage importances shown in Table 5.

Decision-Maker	Cost	Weight	Range	Speed	# Psgrs
1	5.5%	10.7%	13.4%	64.9%	5.5%
2	13.5%	26.0%	45.8%	1.7%	13.0%
3	44.0%	5.7%	19.0%	19.0%	12.3%
4	13.7%	57.8%	10.0%	8.8%	9.7%
5	3.3%	2.2%	10.0%	2.1%	82.4%
6	13.9%	25.8%	25.9%	20.5%	13.9%

Table 5: Criteria Importances for Each Decision-Maker

The preferences (mathematically expressed in the form of an additive multi-attribute utility function) are then applied to construct an ordinal ranking of the 125 different configurations for each decision-maker. Two ordinal ranking profiles are provided, in Figure 9, to demonstrate the effects of criterion weights on utility scores.

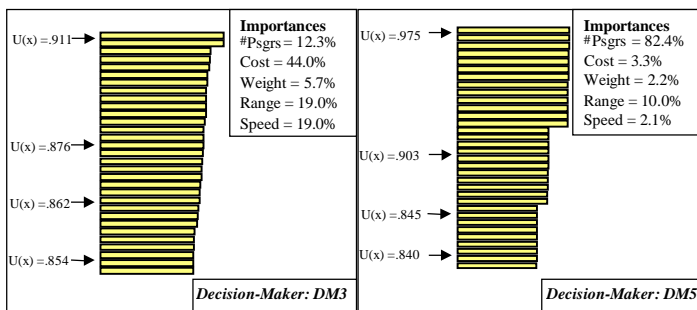


Figure 9. Ranked Alternative Profiles for Two Decision Makers

Decision-maker #3 places higher emphasis on the cost design criteria (44%), whereas, decision-maker #5 placed a significantly higher emphasis on the passenger capacity (82.4%) of the aircraft. This difference in emphasis can be clearly seen in the ranked alternative profiles of the two decision-makers provided in Figure 9. The ranked alternative profile for decision-maker #5 is noticeably ‘stepped’ due to the discrete nature of the design decision problem, and the high emphasis placed on aircraft passenger capacity. Options for passenger capacity include only increments of 500, 400, 300, 200 and 100. Decision-maker #5 had a management background and consequently was very cognizant of aircraft profit. His assessments focused on the number of passengers, which translate into profit for the airline. Having a team member from management was done not only to ensure a more realistic group design scenario, but to also introduce additional conflict between design team members. The ranked

alternative profile, and utility scores, for decision-maker #3 is much smoother in its transition from highest to lowest ranked alternative because of the higher emphasis placed on cost. Cost, despite also being a discrete criterion, is allowed to vary much more than only the 5 increments allowed for passenger capacity.

A ranked order of all 125 airplane configurations is obtained from each of the 6 decision-makers. In preparation for phase 2 of the preference assessment and aggregation, the utilities are normalized, and each decision-maker passes their top 10 alternatives to construct a common set of 50 unique alternatives to pass to the system level designer in Phase 2. In this work it is assumed that the system-level places equal importance on all members of the design team. Therefore, each decision-maker contributes an equal number of personally top-ranked configuration alternatives to the final list. The number of alternatives to pass to the upper-level decision makers is subjective and will depend upon factors such as the computational complexity of evaluating the alternatives, the amount of information the upper-level decision maker wants to handle, and how many total alternatives are possible.

PHASE 2: Process and Results

At this point, the work of the design team is complete, as all necessary information is now in the possession of the system-level decision-maker in the form of a list of unique design configuration alternatives.

In the next and final step of the process, the system level decision-maker selects levels of aspiration which the configuration alternatives are expected to satisfy. These aspiration-levels for each criteria dictate the relative importance of each criterion by evaluating the difference between the aspiration levels and the current alternative levels (Zionts, 1992). The translation of aspiration levels into importances is based on the emphasis placed on each of the design attributes as specified by the aspiration level values. It is similar to the successful multiobjective optimization approach, Physical Programming, which alleviates the need for objective weights and finds the optimal solution based on preference levels (Messac, 1996; Messac, 2000).

Table 6 shows results for eight different evaluation sets conducted by the system-level decision-maker. In each of the different cases, different levels of aspiration are selected, as is evident by the different weighting values found in the left side of Table 6. For example, set 1 places full and sole emphasis on the cost criterion by setting a very high aspiration level for cost. Set 6 places split and nearly equal emphasis on the cost and weight criteria by setting high aspiration levels for both cost and weight, a medium aspiration level for speed and the lowest possible aspiration levels for range and passenger capacity. For each different set of aspiration-levels, a different set of ranked solutions arise as worthy of further attention in the design process.

Set	Sample Importances					Ranked Solutions		
	Cost	Weight	Range	Speed	#Pass	1	2	3
1	1	0	0	0	0	5-4-4	3-4-4	5-4-5
2	0	1	0	0	0	3-4-5	5-4-5	3-4-3
3	0	0	1	0	0	1-1-3	1-1-4	1-1-5
4	0	0	0	1	0	1-1-3	1-1-4	1-1-5
5	0	0	0	0	1	1-1-3	1-1-4	1-1-5
6	.43	.372	0	.198	0	5-4-4	5-4-5	3-4-4
7	.231	.133	.289	.07	.097	3-1-5	3-1-4	5-1-5
8	.271	.109	.362	.151	.107	2-1-5	2-1-4	4-1-5

Table 6: Final ranked design alternative sets

The final ranked solutions appear in the 3 rightmost columns of Table 6. The notation '2-1-5' denotes an airplane consisting of Engine:2, Fuselage:1, and Wing:5. As can be seen from Table 6, depending on the aspiration-levels set up the system level decision-maker, different sets of configurations are recommended as worthy of further investigation in subsequent stages of the design process. It is not coincidence that the top ranked configurations for cost (see set #1 in Table 6) include engine #3 and #5, the two cheapest engines of the engine alternatives, costing \$1.5 million and \$1.0 million respectively.

5 OBSERVATIONS

This paper represents an initial step in a broader research attempt to develop decision support tools for various types of rational group decision making by capitalizing on theoretically sound methodologies in the decision sciences. The theoretical implications of integrating decision support methods is continuing, but at this point, there are some clear advantages to such an integration. The method developed and employed in this paper utilizes concepts from a value-oriented decision approach (Utility Theory) and a goal-oriented decision approach (Aspiration-level Interactive Method) to model the hierarchical designers/manager design problem. Utility Theory is used to construct preference profiles for the individual decision-makers on the design team. Rather than attempting to construct a group preference for all members of the design team simultaneously, the method allowed each decision-maker to construct their own preferred and ranked set of design configuration alternatives for subsequent group aggregation. This aggregation process results in a set of solutions to be presented to the system-level decision-maker with the responsibility of constructing aspiration-levels for the design alternatives to satisfy. The system-level decision maker is allowed complete freedom over the selection of the aspiration-levels, and can change them at any time to explore other regions of the alternatives' solution space.

In the process of carrying out the lotteries, preference profiles, and aspiration level experiments, some general observations regarding design decision making were made:

- A main area of difficulty encountered, not only with this application, but common to many utility theory applications, is accurate and simple assessment of preference profiles. The average preference profile assessment required approximately 15 minutes for the case study.
- An additional insight that was gained was that decisions on monetary scale do not pose the same difficulty as would an analysis on a different scale basis. Even to an aerospace designer/engineer, stating tradeoff preferences between cruise thrust and wing loading is not simple. Therefore, if at all possible, preferences should include a measure of cost.
- Preferences change over time due to various external influences. Therefore, increased accuracy can also be achieved through additional preferences profile assessments for each decision-maker. Applying consistency check to ensure profiles are rational is preferred.
- The case study has been discretized for the purpose of this work. Some solution flexibility has been lost due to this discretization. Parsing the problem further in the utility lotteries (ex: Range $\rightarrow \pm 10$ miles instead of ± 100 miles) would certainly lend more flexibility. However there are two disadvantages to further discretization. First, obviously, is increased computation time. Second, since this is an evaluation and exploration of tradeoffs among alternatives tool, the designer might have a difficulty (or not even bother at all) to assess his preference between Range = 100 miles or 110 miles. The smaller the increment, the more difficult it is for the designer to express his preferences.

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REFERENCES

- Barzilai, J. (1998) "On the Decomposition of Value Functions," *Operation Research Letters*, Vol. 22, pp. 159-170.
- Callaghan, A. (1999) "A 2-Phase Aspiration-Level and Utility Theory Approach to Large Scale Design," Department of Mechanical Engineering. State University of New York at Buffalo, MS Thesis.
- Chen, W., Wiecek, M., and Zhang, J., (1999) "Quality Utility: A Compromise Programming Approach to Robust

- Design”, *ASME Journal of Mechanical Design*, Vol. 121, No.2, pp. 179-187.
- French, S. (1986) Decision Theory: An Introduction to the Mathematics of Rationality. John Wiley and Sons, New York.
- Hazelrigg, G.A. (1996) Systems Engineering: An Approach to Information-Based Design. Prentice Hall Press, New York.
- Keeney, R.L. and Raiffa, H. (1976) Decisions with Multiple Objectives: Preferences and Value Tradeoffs. Wiley, New York.
- Kersten, G.E. (1985) “NEGO-Group Decision Support System,” *Information and Management*, Vol. 8, pp.237-246.
- Luce, R.D. and Raiffa, H. (1957) Games and Decisions. Wiley. New York.
- Messac, A., (1996) "Physical Programming: Effective Optimization for Computational Design," *AIAA Journal*, Vol. 34, No. 1, pp. 149-158.
- Messac, A., (2000) "From the Dubious Construction of Objective Functions to the Application of Physical Programming," *AIAA Journal*, Vol. 38, No. 1, pp. 155-163.
- Ngwenyama, O.K. and Bryson, N. “Eliciting and Mapping Qualitative Preferences to Numeric Rankings in Group Decision Making,” *European Journal of Operational Research*, Vol. 116, pp.487-497.
- Saaty, T.L. (1994) Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process. RWS Publications, Pittsburgh, PA.
- Smith, G. (1999) Logical Decisions Manual. Logical Decisions, Golden, CO.
- Thurston, D.L. (1991) “A Formal Method for Subjective Design Evaluation with Multiple Attributes,” *Research in Engineering Design*. Vol. 3, pp.105-122.
- Thurston, D.L., Carnahan, J, and Liu, T. (1994) “Optimization of Design Utility,” *Journal of Mechanical Design*. Vol. 116, pp.801-808.
- Thurston, D. L. (1999) “Real and Perceived Limitations to Decision Based Design,” *Proceedings of the 1999 ASME Design Engineering Technical Conferences*. DETC99/DTM-8750.
- Tietz, R. and Bartos, O. J. (1983). "Balancing of Aspiration Levels as Fairness Principle in Negotiations," in Aspiration Levels in Bargaining and Economic Decision Making, R. Tietz (ed), Berlin, Springer-Verlag.
- Zionts, S , Stewart, T.J., and Lotfi, V. (1992) “An Aspiration-Level Interactive Model for Multiple Criteria Decision Making,” *Computers in Operations Research*, Vol. 19, No.7, pp.671-681.