

1995 NASA/ASEE SUMMER FACULTY FELLOWSHIP PROGRAM  
JOHN F. KENNEDY SPACE CENTER  
UNIVERSITY OF CENTRAL FLORIDA

APPLICATIONS OF DECISION ANALYSIS AND RELATED  
TECHNIQUES TO INDUSTRIAL ENGINEERING PROBLEMS AT KSC

56-81

7746

P-46

Dr. Gerald W. Evans  
Professor  
Industrial Engineering Department  
University of Louisville  
Louisville, Kentucky

KSC Colleague - Tim Barth  
Industrial Engineering

Contract Number NASA-NGT-60002  
Supplement 19

August 4, 1995

### ACKNOWLEDGMENTS

I'd like to thank Ms. Kari Stiles and Professor Ray Hosler of the University of Central Florida for their administration of the 1995 NASA/ASEE Summer Faculty Fellowship Program. Their attention to detail and the time they spent in arranging various tours and social programs are much appreciated.

The staff of the Industrial Engineering Group at KSC: Tim Barth, JoAnn Leotta, and Amanda Mitskevich provided valuable direction and advice for my work this summer. They are a dedicated group whose work should prove to be very valuable to KSC in the years ahead.

In addition, I'd like to thank Eric Redding for his hospitality, and Kevin Mellet, Cedric Hill, Shelby Roberts, and the other thermal processing system engineers for their help in my understanding of the tile manufacturing process.

Finally, I'd like to thank Linda Tarrence of the University of Louisville and Terrie Bunch of the Kennedy Space Center for typing this report.

## ABSTRACT

This report provides:

1. A discussion of the origination of decision analysis problems (well-structured problems) from ill-structured problems.
2. A review of the various methodologies and software packages for decision analysis and related problem areas.
3. A discussion of how the characteristics of a decision analysis problem affect the choice of modeling methodologies, thus providing a guide as to when to choose a particular methodology.
4. Examples of applications of decision analysis to particular problems encountered by the IE Group at KSC.

With respect to the specific applications at KSC, particular emphasis is placed on the use of the Demos software package (Lumina Decision Systems, 1993).

## SUMMARY

A problem can be defined as a situation in which there is a gap between what is and what should be. Most problems in business and industry originate as ill-structured problems--that is, problems in which the criteria, stakeholders, alternative solutions, etc. are not immediately obvious. A problem formulation process (e.g., involving a procedure such as the Why-What's Stopping Technique) is helpful in defining well-structured problems, in which the criteria, stakeholders, etc., are clearly defined. These well-structured problems originate from ill-structured problems.

A well-structured problem is a decision problem in which one has several alternative problem solutions, each leading to a different outcome (as defined by the performance measures of the situation). The problem then is to select and implement the best alternative solution.

The field of operations research/management science (OR/MS) provides a variety of models and techniques for solving well-structured problems: simulation models, analytic models, gaming models, payoff tables, judgmental models, influence diagrams, decision trees, mathematical programming, goal programming, multiattribute value functions, multiattribute utility functions, and the analytic hierarchy process, to name a few. By listing the characteristics of a problem, relating to the following descriptors: problem importance, number and types of decision makers, number of performance measures, complexity of functional relationships between alternative solutions and the performance measure space, and the amounts of uncertainty/risk associated with various alternative solutions; one can develop guidelines for the selection of appropriate OR/MS techniques.

Many of these OR/MS techniques can be useful tools for the Industrial Engineering Group at the Kennedy Space Center. In particular, those techniques which allow for the consideration of uncertainty/risk in the decision making process (often termed decision analysis techniques) are appropriate for a variety of problem situations. Example applications of these techniques presented in this report include the evaluation and ranking of Phase I SBIR proposals, OMS heater modification benefits analysis, assessment and ranking of proposed modifications of orbiter processing procedures, and the splash vs. NC process decision for the manufacture of orbiter tiles. Implementation of appropriate mathematical models for those decision situations is accomplished through the use of the Demos software package.

## TABLE OF CONTENTS

ACKNOWLEDGEMENTS .....	2
ABSTRACT .....	3
SUMMARY .....	4
LIST OF FIGURES .....	6
1. INTRODUCTION .....	7
2. ELEMENTS OF A PROBLEM AND AN ASSOCIATED SOLUTION METHODOLOGY .....	9
3. FORMULATING WELL-STRUCTURED PROBLEMS FROM ILL-STRUCTURED PROBLEMS .....	13
4. MODELING AND SOLUTION METHODOLOGIES .....	19
5. PROBLEM CHARACTERISTICS AND THE CHOICE OF APPROPRIATE SOLUTION METHODOLOGIES .....	27
6. APPLICATIONS AT THE KENNEDY SPACE CENTER .....	30
7. BRIEF SUMMARY .....	44
REFERENCES .....	45

## LIST OF FIGURES

FIGURE 1. A PORTION OF A GENERIC PROBLEM NETWORK .....	15
FIGURE 2. EXPANDED PORTION OF A GENERIC PROBLEM NETWORK ...	15
FIGURE 3. A TOTALLY EXPANDED GENERIC PROBLEM NETWORK .....	16
FIGURE 4. A HIERARCHY OF OBJECTIVES .....	17
FIGURE 5. AN EXAMPLE OF A DECISION TREE .....	21
FIGURE 6. DEMOS DIAGRAM FOR THE SBIR PROPOSAL RANKING MODEL	33
FIGURE 7. DEMOS DIAGRAM FOR THE OMS HEATER MOD BENEFITS ANALYSIS MODEL .....	35
FIGURE 8. DEMOS DIAGRAM FOR ASSESSMENT OF ORBITER PROCESSING MODIFICATIONS .....	38
FIGURE 9. OVERALL DECISION PROCESS FOR SPLASH VS. NC TILE MANUFACTURING DECISION .....	40
FIGURE 10. NUMERICAL CONTROL TILE PATTERN PROCESS FLOW .....	41

## 1. INTRODUCTION

A problem can be defined as "any situation in which a gap is perceived to exist between what is and what should be," (VanGundy, 1988). One way that a problem can be classified is by the amount of structure contained within it. That is, a problem can be well-structured, semi-structured, or ill-structured. A well-structured problem is characterized by the fact that all of the information required to generate a good solution to the problem is readily available. Such information includes explicit, well-defined criteria, well-defined alternative solutions, etc. An example of a well-structured problem might be the following:

Management has asked you to determine whether an orbiter processing modification should be implemented. The simple criterion specified is a required payback period of one year.

Note that in this problem, the alternatives (implement the modification, do not implement the modification) and the evaluation criterion (required payback period of one year) are well-defined.

Most problems encountered in business and industry are ill-structured problems. That is, the criteria involved in selecting a solution are not explicit, and the various alternative solutions are not easy to come by. An example of an ill-structured problem might involve something like the following situation.

Management has determined that there have been too many incidents involving safety. They have asked you to look into the problem.

Note that in this situation the alternatives and the criteria to use for evaluating alternatives are not immediately obvious. Hence, this is an ill-structured problem.

Operations Research/Management Science is basically concerned with solving well-structured problems. A variety of methodologies, procedures, techniques, algorithms, software packages, etc. have been developed to solve such problems.

The purposes of this report are to illustrate how well-structured problems can be formulated from ill-structured problems; to provide a taxonomy by which problems can be classified; to relate this taxonomy to the variety of OR/MS modeling methodologies and software packages available for use; and to provide example applications for the Industrial Engineering group at the Kennedy Space Center (KSC). The relationship provided between problem taxonomy and OR/MS methodologies should provide the IE group with a set of rough guidelines for the selection of modeling methodologies for solving problems. The emphasis will be on decision analysis methodologies, which explicitly consider the uncertainty/risk aspect of problem solving.

The next section of this report briefly describes the elements associated with problem and their associated solution methodologies. The third section of this report discusses problem formulation/definition, as a way of constructing well-structured problems from ill-structured

problems. Particular emphasis is placed on the Why-What's Stopping Technique, and on the process of structuring objectives and attributes. The fourth section of the report briefly describes various modeling methodologies and techniques, and associated software packages for solving well-structured problems. The fifth section lists and discusses the important characteristics of well-structured problems, especially as they relate to the selection of appropriate modeling methodologies, software packages, etc., listed in the fourth section of the report.

Examples of the uses of some of the techniques for solving various decision problems at the Kennedy Space Center is given in the sixth section of the report. Particular emphasis is placed on applications involving the use of a relatively new software package, Demos, recently acquired by the Industrial Engineering Department. Finally, the last section of the report provides a summary.



## 2. ELEMENTS OF A PROBLEM AND AN ASSOCIATED SOLUTION METHODOLOGY

The elements of a problem and a problem solution methodology can be defined according to the following groups of entities:

1. Decision Makers, Stakeholders, and Analysts.
2. Performance Measures, Objectives, Goals, and Attributes.
3. Alternative (Solutions), Decision Variables, and Design Variables.
4. Constraints.
5. Future States of Nature.
6. Model(s) for Evaluation.
7. Ranking/Optimization Models and Techniques.
8. Implementation Issues.

A decision maker is the person responsible for making the decision about the best course of action (i.e., alternative) for solving a problem. Typically, a problem will have several decision makers. As an example, a group of corporate executives may be decision makers with respect to determining on which projects a comparing should bid.

A stakeholder is one who will be affected by the problem and its ultimate solution, but has no direct say in how the problem should be solved. As such, decision makers should take into account the goals and objectives of the stakeholders in solving a problem. An example of a stakeholder would be someone who owns shares of stock in the company referred to above.

An analyst is a technical expert in solving problems. As such, an analyst helps the decision maker in the structuring of performance measures, and the development of models for problem solution.

Performance measures, objectives, goals, and attributes are all things that can be used to rank alternatives for problem solution. As examples, an objective represents a "direction" for improvement, e.g., minimize cost. A goal represents a desirable level with respect to an objective: obtain a cost of less than \$10,000. An attribute represents a measure for an objective: yearly cost is thousands of dollars.

Typically, a problem has several conflicting objectives which must be considered in the solution process. For example, objectives relating to quality typically conflict with objectives relating to cost. The reasons for these conflicts have to do with the multidimensional nature of products, processes, etc., as well as the varying types of stakeholders which may be associated with a problem.

Attributes may be quantitative or qualitative in nature. For example, prestige on a scale of 0 to 10, with "10" meaning "world-renowned prestige," would be qualitative in nature; yearly cost in thousands of dollars would be a quantitative attribute. In addition, objectives may also be measured by proxy attributes. An example of this would be measuring quality of ambulance

service through the use of response time in minutes. Proxy attributes are often used when an objective is difficult to measure exactly; hence, a proxy attribute measures the degree of achievement of an objective in an indirect fashion.

Alternatives, or alternative solutions, are just different specific approaches for solving a problem. For example, one approach for solving a problem with a factory's production rate would be to implement a new inventory system. Of course, this solution could lead to another problem of choosing the parameter values for the inventory system.

Sometimes complete alternatives are specified as combinations of alternatives. For example, a company may have up to 10 different projects that it can undertake. It can choose none, one, two, etc., or all 10 projects. The combination of projects to undertake is the alternative, and since there are a large number of combinations, there will be a large number of alternatives.

In addition to situations where one would have just a few (e.g., two to ten) alternatives and a large number of alternatives, (e.g., hundreds, thousands, or millions), there are problem situations involving an infinite number of alternatives. This can occur, for example, when one has continuous decision variables. An example of this would be when one must set the velocity of a conveyor.

Constraints are used to restrict the alternatives that one can consider for a problem situation. For example, alternative solutions to a problem may be restricted by the fact that no alternative may have an initial cost of greater than five million dollars, regardless of the future profits resulting from that alternative.

Future states of nature can basically be represented as parameter values, over which the decision maker has no control, that can affect the outcome (i.e., performance measure values) associated with an alternative. For example, the cost savings associated with a suggested change in a maintenance activity for the orbiter is dependent upon the number of times that the activity is to take place, which, in turn, is dependent upon the number of orbiter flows. Since the number of orbiter flows is not under the control of the decision maker, it is an uncertain quantity, and its value does affect the outcome (i.e., cost savings) associated with implementing the change, it is a state of nature.

One of the primary tasks associated with problem solving is identifying the future states of nature and determining the likelihoods (i.e., probabilities) associated with these states. The uncertainty associated with the state of nature can result in uncertainty associated with the outcome associated with an alternative.

A model for evaluation is basically a way to map alternative solutions into the outcome space (i.e., attribute values). The outcome associated with the alternative may be either deterministic or probabilistic in nature, depending on the states of nature that exist. A wide variety of modeling methodologies are available for evaluation, including analytic models, simulation models, gaming models, and judgmental models (Miser and Quade, 1985). An example of part

of an analytic model would be an equation which relates the cost associated with performing some procedure to the number of times that the procedure is performed.

The evaluation model used for a particular situation is dependent upon the complexity of the relationships between the alternative chosen and the attribute values. For example, in a factory, the relationship between the numbers of machines in various work centers and the production rate is a complex one. In order to establish this type of relationship, one must usually develop a simulation model of the factory under study.

As another example, the relationship between the number of direct man-hours saved from the elimination of some procedure and the total cost savings associated with the elimination could probably be written in the form of a single linear equation:

$$S = atx + bmx$$

where

- S = total cost savings
- x = number of hours saved from the elimination of the procedure
- t = the number of times that the procedures would have been performed
- a = the cost per hour for direct manhours
- m = the number of indirect manhours required per direct manhours
- b = the cost per hour for indirect manhours

Ranking/optimization models and techniques are used to rank alternative outcomes and /or choose the best feasible outcome (associated with a particular alternative). These models/techniques are sometimes "part of" evaluation models. For example, a linear program is a model which evaluates; and, with the revised simplex method as an optimization technique, allows one to find an optimal solution to the linear program. "Sophisticated" ranking/optimization models and techniques are only needed when either of the following two condition exist:

1. There are too many alternatives involved (e.g., as a result of the use of continuous decision variables or combinations) to allow a complete evaluation of each of them.
2. The evaluation model allows for multi-attributed output and/or uncertainty in the outcome.

When neither of the above two conditions holds, then the ranking of alternative outcomes is a simple process. For example, if the sole criterion or attribute is to maximize the predicted (deterministic) net present worth of the chosen alternative, and there are only four alternatives to consider, then the alternatives can just be ranked in order of decreasing net present worth.

If both conditions listed above exist in a problem situation, then two types of processes are

required of ranking/optimization models and techniques: an optimization process (for the first condition) and a preference structuring process (for the second condition). The optimization function is required when there are just too many alternatives to allow a complete evaluation of each alternative. Optimization techniques are typically associated with mathematical programs--linear programs, nonlinear programs, integer programs, etc. A preference structuring function is required when one has multiple, conflicting objectives to consider and/or probabilistic outcomes. Examples of models/techniques which one can employ in these areas include the scorecard approach; payoff tables; various optimization techniques such as revised simplex, interior point methods, branch-and-bound, dynamic programming, etc.; lexicographic ordering; goal programming; multiobjective mathematical programming; multiattribute value functions; multiattribute utility functions; and, the analytic hierarchy process. Ranking/optimization models and techniques are discussed in greater detail in Section IV of this report.

Finally, issues involving implementation of a selected alternative are often neglected. In fact, little attention is given to this important area in the OR/MS literature. Suffice it to say, however, that the implementation process becomes much simpler when one has a good solution (as a result of a good problem formulation) and has kept the decision makers heavily involved through the problem formulation and solution processes.

### 3. FORMULATING WELL-STRUCTURED PROBLEMS FROM ILL-STRUCTURED PROBLEMS

The steps associated with solving an ill-structured problem are (page 122 of Miser and Quade, 1985):

1. Formulation/definition of the problem.
2. Generation of alternatives.
3. Forecasting future "states of nature".
4. Identifying the consequences associated with the alternatives.
5. Comparing and ranking alternatives.
6. Implementation of the selected alternative(s).

The step which results in most of the difficulty associated with problem solution is problem formulation/definition. That is, most people in solving ill-structured problems do not correctly identify the problem, and hence, their "solution" does not address the real problem. Instead, what's often done is that a problem symptom is identified as a problem. Hence, correct problem formulation is a crucial, perhaps the most crucial, aspect of problem solving. As noted by Ackoff (page 8, 1974):

"We fail more often because we solve the wrong problem than because we get the wrong solution to the right problem."

Formulation of a problem will provide, among other things (Miser and Quade, 1985):

1. A list of decision makers and stakeholders.
2. A preliminary list of objectives and attributes.
3. A specification of some promising alternatives.
4. A definition of at least some of the constraints.
5. A specification of the states of nature.
6. Specification of the types of evaluation and criterion models that one might use.
7. A plan for the analysis.

Note that some of these specifications may be very general in nature. For example, one alternative for solving a problem in a manufacturing system might be to install a new inventory control system. The specification of the parameters of the system might not come until later, or not at all, depending on whether or not the alternative was later rejected from consideration. The point here is that the problem formulation stage of the problem solution process is dynamic in nature. Objectives/attributes can be revised, alternatives can be more specifically defined, constraints can be relaxed, etc.

The problem formulation stage should be approached cautiously, because the aim is to develop an appreciation for the problem context, and to not impose a rigid structure on the problem (page 153, Miser and Quade, 1985).

A variety of techniques have been developed for problem formulation, including the Why-What's Stopping Technique (Basadur, Ellspermann and Evans, 1994), mind mapping (Chapter 12 of Wilson, 1993), cause and effect diagrams (Chapter 13 of Wilson, 1993), the Five W's and H Technique (Chapter 3 of VanGundy, 1988) and Dimensional Analysis (Chapter 3 of VanGundy, 1988). All of these techniques basically represent ways of structuring the brainstorming process. In addition to the references listed above, see Chapter 5 of Miser and Quade (1985) and Chapters 2, 3, and 4 of Schoenauer (1981) for further discussion of these and other problem formulation techniques. Further discussion of the Why-What's Stopping Technique is given below.

#### The Why-What's Stopping Technique

As noted earlier, no problem exists in isolation but is actually a part of a system of problems, called a *problematique* by the French or a "mess" by Ackoff (1974). In order to be sure that he/she is attacking the right problem, and in order to generate good initial sets of objectives/attributes, alternatives, etc., the analyst and decision makers should be aware of this system of problems.

The Why-What's Stopping Technique (Basadur, Ellspermann, and Evans, 1994) is one approach for generating this system of problems. As a byproduct, one often also obtains objectives/attributes, initial alternatives and constraints, etc. from the use of the technique. In addition, when there are multiple decision makers for a problem, this technique can be an excellent vehicle for communication among the decision makers.

The why-what's stopping technique involves a facilitator and a group of decision makers and stakeholders meeting for a brainstorming session. The output of the session is a "network" of related problems, which will implicitly contain a set of objectives/attributes, preliminary alternatives, constraints, etc. By a network, we mean a system of "nodes" (each node being a problem statement) connected with lines. A line connecting two nodes implies a direct connection between those two problem statements.

The session commences, following an explanation of the technique by the facilitator, with a brief statement of what is thought to be the problem by one of the participants (stakeholder/decision maker). The facilitator will write that statement on a blackboard (or some other device), and ask the group the answer the question:

"Why is this (the initially stated problem) a problem?"

After receiving an answer from one of the participants, the facilitator might continue to ask the question:

"Why else is this a problem?"

referring to the original problem statement.

What would be obtained following this would be a portion of a problem network as shown in Figure 1, where PS1 was the initial problem statement, and PS2 was an answer to the question: "Why is this a problem?" and PS3 and PS4 are answers to the questions "Why else?"

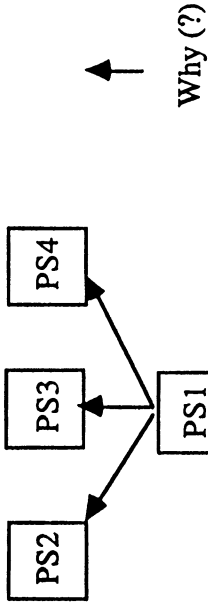


Figure 1. A Portion of a Generic Problem Network

At this point, the facilitator (with input from the participants) could continue to ask "why else" questions in relation to the initial problem statement (PS1), or he/she could select one of the other problem statements (e.g., PS3) and commence the why-why else questioning process all over again. Hence, the facilitator might have a network like the one in Figure 2.

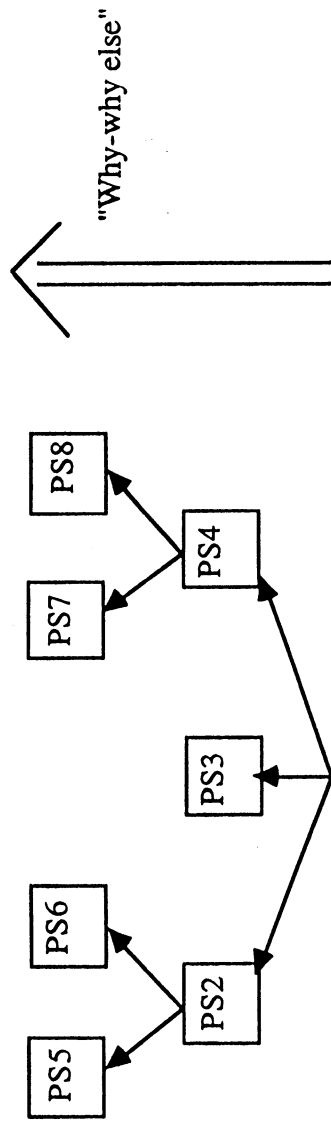


Figure 2. An Expanded Portion of a Generic Problem Network

After a "sufficient" expansion in the upwards direction through the "Why-Why else" questioning process, the facilitator may wish to expand the network in the other direction. This can be accomplished by asking the question:

"What's Stopping us from solving this problem (e.g., problem PS1)?"

This question is usually asked in relation to the initial problem statement (PS1), but it could be asked in relation to any of the other problem statements.

Following this process, one should have a problem statement network which would appear something like the one in Figure 3.

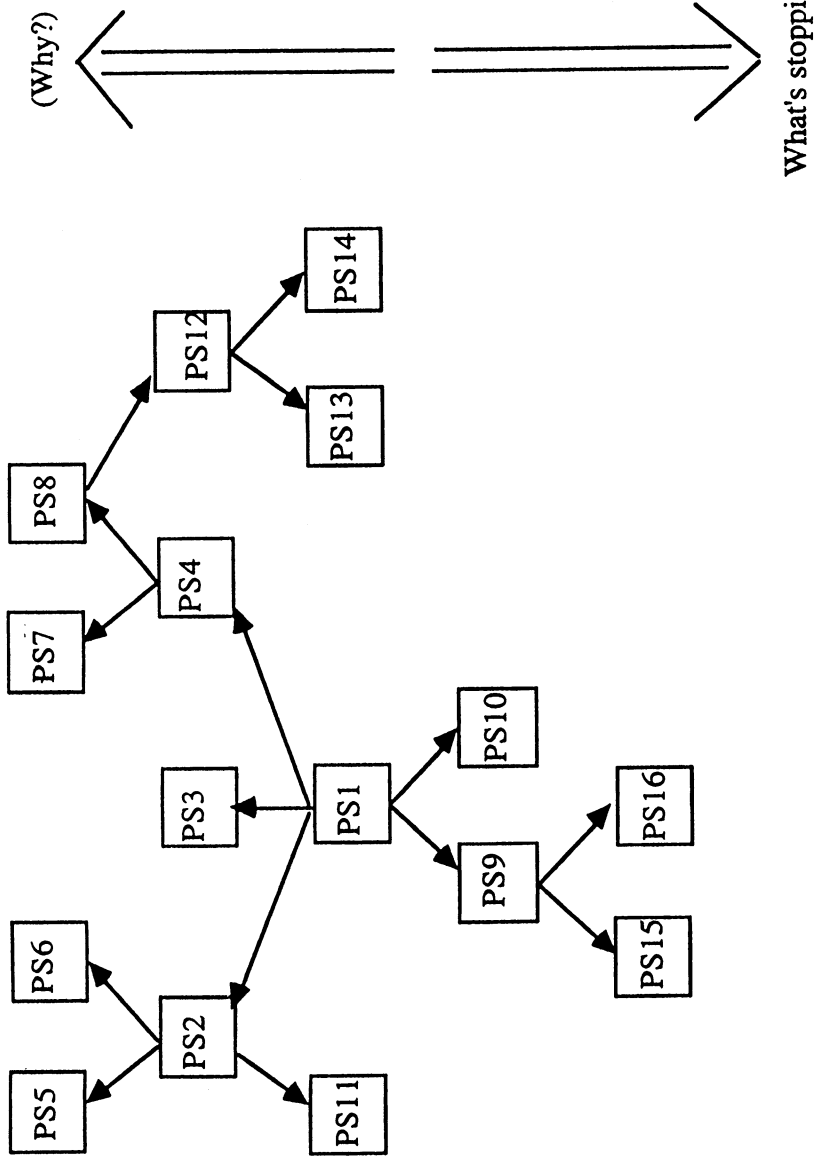


Figure 3. A Totally Expanded Generic Problem Network

Note that an answer to a "why" question is indicated by an upward arrow, and an answer to a "what's stopping" question is indicated by a downward arrow. The facilitator must use his/her experience (with appropriate input from the participants) to decide how far to expand a particular branch of the network. The basic criterion has to do with whether the participants are getting outside the scope of their responsibility. Answers to the "why" question basically result in an expanded problem scope, while answers to the "what's stopping" question result in condensing the problem area, even leading to specific alternatives for problem solution.

The exercise also leads to the realization that there is a fine line between alternative solutions and objective/attribute measures. For example, an answer to the question of

"What's stopping us from improving quality?"

might be:

"A lack of well-trained inspectors."

This leads one to suspect that an alternative solution might be:

"Get more well-trained inspectors."



In addition, in a different, but related, problem context, the number of well-trained inspectors might be an attribute, associated with the problem of developing a plan for increasing the number of well-trained inspectors.

One other activity which the facilitator does is reframe the problem into an "opportunity" or at least a more optimistic statement, by attaching the phrase: "How might we" at the beginning of each problem statement. For example, instead of writing:

"A lack of well-trained inspectors," the facilitator would write:

"How might we increase the number of well-trained inspectors?"

on the blackboard.

Structuring Objectives and Attributes

Objectives and attributes for a problem typically fall into a "hierarchy". At the top of the hierarchy are the more general objectives, while towards the bottom of the hierarchy are the more specific objectives. Finally at the bottom of the hierarchy are the specific attributes, each one connected to a specific objective. As an example, consider the hierarchy below, reprinted from page 105 of French (1986).

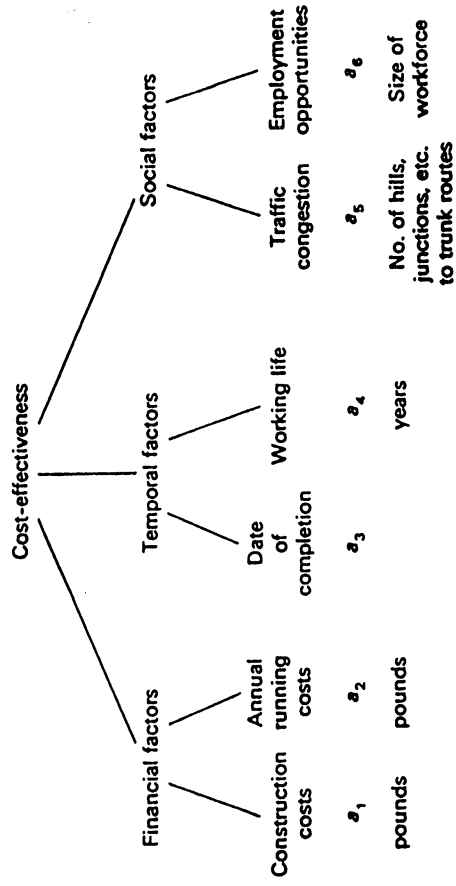


Figure 4. A Hierarchy of Objectives

Note that at the top of this hierarchy is the overall objective: optimize cost-effectiveness. This overall objective is achieved by optimizing financial factors, temporal factors, and social factors. Optimizing financial factors means minimizing construction costs and minimizing annual running costs. Attributes are used to measure the lowest level objectives. For example, the objective of minimization of construction cost is measured by construction costs in dollars. Construction of a hierarchy is an important aspect of problem definition. A set of lower level objectives can be attained from a higher level objective by asking a question such as:

How do we achieve (the higher level objective)?

For example, the way to optimize financial factors is to minimize construction costs and to minimize the annual running costs.

The question of how far to extend a hierarchy for a particular problem is subjective in nature, relating to several different aspects of the problem (e.g., the orientation of the decision maker--quantitative or nonquantitative; the nature of the evaluative models to be used; etc.). If one does not extend the hierarchy very far then, typically, the attributes that would be used to measure the associated higher level objectives would be subjective in nature. See Chapter 2 of Keeney and Raiffa (1993) for further discussion on construction of a hierarchy.

Attributes associated with the lowest level objectives of a hierarchy may be either quantitative or nonquantitative (i.e., subjective) in nature. Quantitative attributes (e.g., construction cost in current dollars) can typically be used when the hierarchy is extended to include very specific objectives. Nonquantitative, or subjective, attributes are used when the hierarchy is not extended very far; i.e., when the lowest level objectives of the hierarchy are subjective in nature.

Obviously, there are tradeoffs associated with the decision of how far to extend a hierarchy. For example, if one does not extend the hierarchy very far, one will have the advantage of having to deal with only a very few attributes. However, these attributes will probably be subjective in nature. If one does extend the hierarchy very far, then there may be many attributes to deal with in the analysis (a disadvantage); however, these attributes will probably be quantitative in nature.

#### 4. MODELING AND SOLUTION METHODOLOGIES

As discussed earlier, there are two types of models and associated solution methodologies required for solving a well-constructed problem: evaluation models and associated solution methodologies, and ranking/optimization models and associated solution methodologies. This section of the report discusses several types of these models and solution methodologies, as well as associated software packages.

A model refers to a representation of a system and/or a decision maker's preference structure over the outcome space, while a solution methodology refers to how you experiment with (or solve) the model in order to select a best alternative solution to the problem.

Evaluation models provide a mapping from the alternative space to the outcome space (as measured by the attribute values). For example, in a problem situation involving a modification to orbiter processing procedures, the two alternatives to consider would be:

1. Do not implement the modification.
2. Implement the modification.

The objective that might be considered here would be:

Maximize the net present worth of expected savings.

Hence, one would need some type of evaluation model (represented as a sequence of equations) which would output the net present worth of expected savings as a function of the proposed modification.

The various types of models, methodologies, and techniques from operation research cannot be easily classified as either evaluative in nature or optimization-based in nature; often, a particular type of model allows the performance of both functions. However, the emphasis is usually on one area or the other.

For the purpose of this report, we will classify the following types of models as emphasizing the evaluative process: simulation models, analytic models, gaming models, judgmental models, decision trees, influence diagrams, and decision tables. These model types are discussed below.

Simulation models are useful evaluation tools when a detailed representation of a process is required. As defined by Pegden, Shannon, and Sadowski (1990), simulation is "the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system and/or evaluating various strategies for the operation of the system." Simulation models are characterized by the fact that they contain no inherent sophisticated optimization capability, and that their outputs are typically multiattributed, probabilistic outcomes.

Usually, several different statistical problem must be addressed when one is using a simulation model. One reason for this is that one run of a simulation model corresponds to a statistical experiment. Examples of statistical problems that one must address when using a simulation model include input modeling (fitting distribution functions to data), generating samples from probability distributions, setting initial conditions for the simulation runs, determining a "warm-up period" for the run, and various problems related to interpretation of output--estimating expected values and variances, determining confidence intervals, hypothesis tests, and ranking probabilistic outcomes with a specified degree of confidence. See Law and Kelton (1992) for further discussion of these and other statistical concepts.

A variety of software packages have been developed to aid in the simulation modeling process. In fact, the number of these packages has grown tremendously in the last 10 years, indicating the popularity of this modeling methodology. A good source for detailed descriptions of many of these software packages is the Software/Modelware Tutorial Section of the annual Proceedings of the Winter Simulation Conference.

A few years ago, one could classify these simulation software packages as being either simulators (in which no programming was required to build a model) or simulation languages. Recently however the distinction between these two categories has blurred. For example, the Arena package of System Modeling Corporation allows programming inserts which make it extremely flexible. Examples of some of the other simulation software packages include SIMAN/Cinema, SLAMSYSTEM, GPSS, SIMSCRIPT, WITNESS, PROMOD, MODSIM, Taylor II, etc. See Pritsker (1995) for additional discussion on simulation.

In an analytic model, mathematical statements are used to represent the relation that hold between the variables of interest (page 195, Miser and Quade, 1985). These models typically do not represent a system in as much detail as a simulation model, hence they are typically not as accurate as simulation models. Instead, analytic models represent a system as a group of (either simultaneous, or serial) equations.

In addition to consisting of either a simultaneous or serial system of equations, analytic models can be either deterministic or probabilistic in nature. If the system is probabilistic in nature, then typically one may need to employ some type of sampling procedure in the solution process. The Demos software package (Lumina Decision Systems, 1993) is an example of a package which will solve a probabilistic analytic model consisting of a series of equations.

Basically, whenever the relationship(s) between a set of alternatives and the chosen attributes/objectives can be represented as closed form equations, then an analytic model can be used. If the relationship(s) cannot be represented in this fashion, or are not even known, then one may have to employ a simulation model.

Analytic models can be useful in the calculation of economic performance measures such as net present worth, or in solving inventory control problems, queueing problems, and network flow problems. Mathematical programs are basically analytic models.

A gaming model is a form of simulation modeling where the people involved with the system under study simulate the behavior of major elements of the system. Typically, these models require much effort to develop since they require interaction between humans and computers. Gaming models, which have been used extensively by the military establishment, are quite useful as training tools and to improve communication among players of different disciplines. See pages 197 to 199 of Miser and Quade (1985) for further discussion of gaming models.

Judgmental models basically involve gathering a group of experts to forecast the outcomes associated with various alternative problem solutions. These models can be useful when there is little data available for building simulation or analytic models. The various types of judgmental models differ in the way they structure the group discussion. Examples of techniques associated with judgmental modeling include scenario writing (see Section 9.5 of Miser and Quade, 1985), the Delphi technique (Linstone and Turoff, 1975), cross-impact analysis, and various team and workshop approaches.

In problem situations where the alternatives are expressed in terms of sequences of interrelated decisions, a decision tree may be an appropriate modeling technique. These decision trees explicitly account for uncertain factors in the decision making process, as illustrated by Figure 5, reprinted from page 260 of French (1986).

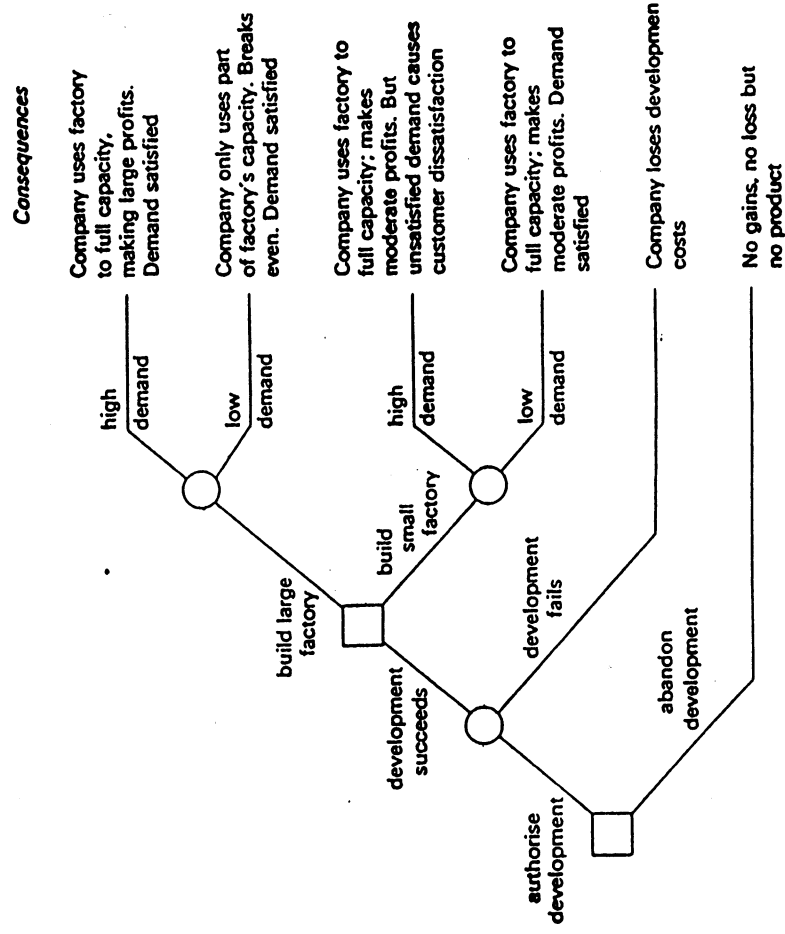


Figure 5. An Example of a Decision Tree (page 260, French, 1986)

In this problem, the initial decision to be made (authorize or abandon development) is dependent upon the outcomes associated with later decisions. In addition, the problem includes probabilistic events (e.g., development succeeds or development fails) over which the decision maker has no control. A decision tree analysis would indicate which decision is the best to take initially.

An influence diagram might be thought of as a generalization of a decision tree, in which the influences which affect variables are indicated through a graph of nodes and arcs. The nodes represent the variables and an arc leading from one node to another indicates that the first variable has an affect on the second. The software package, Demos, utilizes the concept of influence diagrams. Other software packages which model decision trees and/or influence diagrams include DPL, Arborist, and Supertree. See recent issues of the journal QR/MS Today for reviews of these and other software packages for decision analysis. In particular, see the article by Shachter (1986) or Bunn (1984) for further information on influence diagrams.

The scorecard approach to problem solving (see pages 231 to 236 of Miser and Quade, 1985) is fairly informal in nature. In this approach, all of the consequences associated with an alternative (quantitative or qualitative in nature) are displayed in a tabular array. Probabilistic consequences are also displayed. In the tabular array, the entries in each column represent the consequences associated with an alternative, while the row entries show how a particular consequence varies from one alternative to the next. The decision makers gather in a room, develop the scorecard, and decide on the best alternative through a discussion process.

Scorecard approaches are appropriate when there are only a few alternatives (say 10 or fewer) to consider, when there are several decision makers, and/or when there are many attributes, at least some of which may be probabilistic in nature.

A construct which is somewhat similar to a scorecard is the decision table (page 163 of French, 1986). A decision table shows the outcome associated with each alternative for each state of nature. Once the alternatives have been expressed in terms of a decision table, one can employ any of several different criteria for selecting an alternative, including Wald's maximim return, Hurwicz's optimism-pessimism index, Savage's minimax regret, and Laplace's principle of insufficient reason (see pages 36 to 39 of French, 1986). One could also employ a more sophisticated approach, involving a multiattribute utility function, to be discussed later.

Ranking/optimization models/processes include multiattribute value functions, multiattribute utility functions, the analytic hierarchy process, and various types of mathematical programs (linear programs, integer programs, dynamic programs, multiobjective mathematical programs, etc.). The first three of these: multiattribute value functions, multiattribute utility functions, and the analytic hierarchy process concentrate on modeling the decision maker(s) preference structure over a multidimensional, possibly probabilistic, outcome space.

A multiattribute value (MAV) function is a function which maps scores over multiple attributes into an interval of the real number line, usually [0,1]:

$$V: x_1, x_2, \dots, x_n \rightarrow [0,1]$$

where  $x_1, x_2, \dots, x_n$  are the  $n$  attribute values. A MAV function has the property that if the decision maker prefers one outcome to another, in terms of its multiple attribute values, then the MAV function value associated with the first outcome will be higher than the value associated with the second outcome. In symbolic terms:

$$v(x_1', x_2', \dots, x_n') > v(x_1'', x_2'', \dots, x_n'')$$

if and only if

$$v(x_1', x_2', \dots, x_n') > v(x_1'', x_2'', \dots, x_n'')$$

where the symbol ">" means "is preferred to."

Once a MAV function has been developed, instead of optimizing over  $n$  attributes, one only has to optimize over one measure.

MAV functions are formulated through interview sessions between the analyst and the decision makers, in which the decision makers must answer hypothetical questions concerning his/her tradeoffs over multiple, conflicting objectives. Note that two different rational and reasonable decision makers could have different MAV functions, depending on how they value the different objectives. See Chapter 3 of Keeney and Raiffa (1993) for more information on MAV functions.

A multiattribute utility (MAU) function represents a generalization of a MAV function in that it allows a ranking of alternatives in situations with multiple objectives and uncertainty/risk. More formally, a MAU function is a mapping from an  $n$ -dimensional attribute space:  $x = (x_1, \dots, x_n)$  to a closed interval:  $[0, 1]$  of the real number line. It has the property that:

$$\bar{x}' > \bar{x}'' \text{ if and only if } Eu(\bar{x}') > Eu(\bar{x}'')$$

where  $\bar{x}'$  and  $\bar{x}''$  are two different  $n$  dimensional probabilistic outcomes and  $Eu(\bar{x}')$  and  $Eu(\bar{x}'')$  are the expected utilities associated with those outcomes, respectively. The above basically says that the decision maker prefers outcome  $\bar{x}'$  to outcome  $\bar{x}''$  if and only if his/her expected utility for outcome  $\bar{x}'$  is larger than the expected utility for outcome  $\bar{x}''$ .

Assessment of a MAU function is usually much more difficult than the assessment of a MAV function since the decision maker must answer questions about hypothetical situations involving multiple objectives and uncertainty/risk. See Keeney and Raiffa (1993) or French (1986) for

further information about MAU functions.

A MAU function can be an excellent device for ranking outcomes involving multiple objectives and uncertainty/risk. They can be used in conjunction with other methodologies such as simulation, decision trees, influence diagrams, and decision tables. In addition, just the assessment process by itself can be useful in helping the decision makers to think about their preferences in a structured fashion.

The analytic hierarchy process (AHP) relies on the development of a hierarchy of important problem factors (e.g., objectives or attributes) to rank alternatives over multiple attributes. In the hierarchy, the higher level objectives are at the top of the hierarchy, while the lower level objectives are towards the bottom. The second lowest level of the hierarchy will typically consist of problem attributes while the lowest level will consist of the various alternatives. Through sets of pairwise comparisons of the factors at each level of the hierarchy, local and global weights, reflecting importance, are computed for each element of the hierarchy. The global weights computed for the respective alternatives are the scores for those alternatives--the higher an alternative's score, the more desirable that alternative is.

AHP is implemented in a software package called Expert Choice, advertised in OR/MS Today. The score by AHP for an alternative is comparable to the score that the alternative would receive through the use of a MAV function. AHP is typically easier to use for a ranking process than a MAV function, because of the difficult assessment process associated with a MAV function. However, there are theoretical problem associated with AHP, as reported in the literature (e.g., see various issues of Management Science). One of the most basic problems with AHP is that the decision maker must answer questions such as:

"How much more important is safety than cost?"

without the use of any type of scale. A MAV function assessment on the other hand involves asking the decision maker detailed questions concerning tradeoffs between specific outcomes, e.g.:

"How much would you be willing to pay in order to decrease the probability of serious injury in a particular year from .00001 to .000009?"

In summary, if an accurate representation of the decision maker's preference structure is needed, then a MAV function is probably more appropriate to use than AHP. If one needs a quick answer to a problem, than AHP is probably more appropriate. See Saaty (1988) for further discussion of AHP.

None of the three approaches discussed above (MAV functions, MAU function, or AHP) include any inherent optimization capability. When there are a small number of alternatives to consider (e.g., 10 or fewer) no sophisticated optimization capability is needed, and a "complete enumeration" of all of the alternatives can be performed. When there is a large number or even



an infinite number of alternatives, some type of implicit enumeration is needed. This turns out to be the case when one has combinations of things to consider or there are continuous decision variables to consider. Examples of the first situation (combination) would be the following:

1. A committee has 100 different (but dependent) processing enhancement suggestions to consider. Any number and combination of suggestions can be implemented; hence, the number of alternatives is actually the number of combinations ( $2^{100}$ ) to consider.
2. Shuttle processing requires literally thousands of activities. The timings (when they are performed) of these activities are important decisions to be made. The timing/sequence of activities is restricted by precedence relationships (e.g., it's necessary to inspect some item before it can be replaced/repaired), resource constraints (e.g., the number of technicians available is limited), or capital constraints, among other types of restrictions. However, at any particular point in time (e.g., 7 am on August 7) there still may be dozens of activities from which to choose. The various alternatives in this case correspond to the combinations of activities that can be performed at any particular point in time. Note that this is an ongoing decision problem for any large project, and that this area of research (resource-constrained project scheduling) has been addressed extensively in the literature.

An example of a continuous decision variable would be the determination of the length of time to test some item. Since this length of time is continuous, the number of alternatives is, in effect, infinite.

A wide variety of mathematical programming models allows one to represent optimization situations like the ones described above. Examples of these mathematical programs include linear programs, integer programs, dynamic programs, goal programs, and multiobjective mathematical programs. See Nemhauser (1989) for further discussion of some of these models.

A survey of the literature reveals the existence of a large number of sophisticated optimization techniques for solving optimization problems. These techniques can be categorized as being either heuristic or exact in nature.

Heuristic optimization techniques are those which give a good, though not necessarily optimal, solution to a problem. One advantage of these techniques is that they are usually easy to understand and explain to others. They do not usually require any type of sophisticated mathematical formulation of the decision problem, and can usually be easily implemented on a computer. One example of a heuristic optimization technique would be to evaluate 1000 alternative, randomly chosen, solutions to a problem (out of say approximately one million feasible alternative solutions), and then select the best one out of the 1000 to implement.

Resource-constrained project scheduling is an example of an area which relies heavily on heuristic optimization techniques. Many of these techniques have been implemented in several

different software packages for project scheduling.

Numerical search procedures for solving nonlinear optimization problems is another example of a body of techniques that can be thought of as being heuristic in nature. These procedures typically have somewhat subjective termination criteria, and in addition, usually achieve, at best, a local optimum to a problem.

Examples of exact optimization techniques include those often associated with mathematical programming models: linear programs (revised simplex method, interior point methods), integer programs (branch-and-bound methods, dynamic programming), nonlinear programs (methods based on differential calculus, dynamic programming). These complex techniques are often difficult to explain to others, and often require the formulation of the problem into one of the mathematical constructs listed above. Sometimes exact techniques can be used in a heuristic fashion; for example, one has the option in a branch-and-bound procedure (for solving an integer program) to terminate the procedure when the algorithm has achieved a solution that is within  $x\%$  of an optimal solution in terms of the objective function value.

The choice of which optimization technique to choose for situations where there are a large number of alternative is, of course, somewhat subjective in nature. When the evaluation model is very complex (e.g., highly nonlinear or not even of a closed-form), then one would probably want to use a heuristic optimization technique. A situation involving the use of a simulation as an evaluation model is one where the model would not be of a closed form, and hence one may want to use a heuristic technique.

When the evaluation model can be formulated as a mathematical program, then the possibility of using an exact optimization technique exists. Typically, however, such an optimization technique can only be implemented through the use of an "expensive" software package, such as CPLEX for solving linear program or integer programs. See various issues of the journal OR/MS Today for description of the various software packages available for the optimization process. See Nemhauser (1989) for further discussion on optimization techniques.

Several of the models and associated solution methodologies can be incorporated into a single decision support system for a particular problem situation. For example, it may be reasonable to combine a simulation model with a utility function and a numerical optimization technique in order to select a best solution to a problem with multiple objective and uncertain outcomes. The best techniques to use for a particular problem depend upon the characteristics of that problem, discussed in the next section of this report.

## 5. PROBLEM CHARACTERISTICS AND THE CHOICE OF APPROPRIATE SOLUTION METHODOLOGIES

In this section of the paper we briefly discuss the important characteristics of a problem which affect the methodologies chosen to solve that problem.

Problem importance is probably the major characteristic associated with the choice of techniques/methodologies for solving a problem. Importance can be measured in terms of performance measures related to cost, schedule, safety, etc. or in terms of political pressures (e.g., who in the organization is interested in the problem). Obviously the amount of time and money that one will spend in solving a problem (and hence, the solution methodologies chosen) should depend on problem importance.

The number and types decision makers involved in a problem is also an important problem characteristic. The predisposition of the decision maker(s) towards the use of quantitative techniques is an important factor to consider, especially as it relates to the choice of a preference structure model. (Note that while it is important for the decision maker to be involved in building both the evaluation models and the preference structure models, this involvement is more crucial in terms of the preference structure models). Also, the larger the number of decision makers involved in a problem, the more difficult that situation. Most methodologies/techniques for development and analysis of preference structure models make the assumption that there is only one decision maker. For example, the procedure for formation of a multiattribute value or utility function assumes that there is one decision maker answering a question concerning tradeoffs among performance measure. If there were multiple decision makers, an analyst would basically have two choices:

1. Assemble the decision makers as a group and, for each question regarding hypothetical tradeoffs, have them provide a consensus answer.
2. Assess a value/utility function for each decision maker, and then rank the alternatives for each decision maker.

In the second case, the decision makers would meet as a group and discuss their individual rankings in order to arrive at a consensus first choice alternative. Hopefully, the individual ranking would not differ from each other too much.

Of the two approaches listed, the first one would be the preferred approach with respect to time and effort, especially if there were not too many decision makers.

The number of attributes associated with the problem affects both the type of evaluation model(s) and the type of ranking/optimization model(s) used for problem formulation. Note that often an analyst will have much leeway with respect to the number of attributes used in the analysis, depending upon how far down the hierarchy of objectives/attributes he wishes to move. In cases where only a very few attributes are used in the analysis (say, one to three), the attributes themselves may be very subjective in nature. Hence, it may be difficult to get a good,

"quantitative," evaluation model; what may be used instead is a judgmental model to relate alternatives to attribute values.

An example of this situation may be one where a department must rate Small Business Innovation Research (SIR) Program proposals, over four subjective attributes: scientific/technical merit, anticipated commercial applications, qualification, and merit of proposed work plan. In this case, the alternatives are the individual proposals, respectively, and the evaluators, through their mental models, give scores to each of the proposals over each of the attributes.

Of course, there may also be situations with a very few attributes where these attributes are quantitative in nature. In these situations, more sophisticated quantitative models (e.g., simulation or analytic models) may be used.

Also, in situations where there are very few attributes, the preference structure model used can typically be very sophisticated (e.g., a multiattribute utility or value function). The reason for this is that the amount of "preference" information required to assess a multiattribute utility or value function becomes onerous as the number of attributes becomes large.

In situations where the analyst decides to use a large number of attributes (either because the problem situation calls for it, or for more arbitrary reasons), the attributes themselves may very well be quantitative in nature; hence, a sophisticated, and explicit, quantitative evaluation model may be appropriate. However, as discussed above, a sophisticated preference structure model (e.g., a multiattribute value or utility function) would be very difficult to develop in situations involving a large number of attributes. In this case, therefore, the decision maker may want to use a scorecard approach (Miser and Quade, 1985) or a constraint-based approach, as discussed below.

There are many different constraint-based procedures that one could employ when there are many attributes to consider. For example, the analyst might assess a utility/value function over one or two of the more important attributes, and then constrain the other attribute values to attain particular levels. The approach may be "interactive" in nature in that the decision maker(s) may vary the goal levels, similar to one of the approaches involving multiobjective mathematical programming.

The complexity of the relationships between the alternatives and the outcomes and the amount of hard data available to assess these relationships affects the choice of the type of evaluation model used. For example, if there is little or no data available, and the relationship is a complex one, then judgmental model(s) may have to be used. This may be the case if the alternative being evaluated relates to a completely new type of system.

If the relationship(s) are complex, yet the processes which give the relationships are well-understood, then a simulation model may be appropriate to use as an evaluation tool. If the relationship(s) are well-understood and can be written as a series of equations, then an analytic

model may be appropriate.

The amount of uncertainty/risk involved in the relationship between the alternatives and the outcomes can affect the type of evaluation model used and the methods used to experiment with the model. For example, simulation models are excellent choices for representing the uncertainty in a system. However, if a simulation model cannot be used, then sensitivity analysis of an analytic model may be appropriate for analyzing how changes in inputs can affect the outputs associated with a system.

The number of alternatives under investigation affects the choice of a ranking/optimization model and associated solution technique. For example, when there are only a very few alternatives to consider (e.g., ten or fewer) then a complete enumeration of all alternatives can be performed - no sophisticated optimization procedure is needed. In cases with many alternatives (as a result of continuous decision variables or combinations of decisions) some type of efficient representation of the alternatives is needed, as well as a sophisticated optimization technique.

There are several other considerations that could affect the choice of modeling techniques. In particular, the time available to solve a problem affects the choice, as well as whether or not the problem situation is an ongoing one. For example, if one does not have a lot of time to solve the problem and there is little or no data available to help in the development of an evaluation model, then a judgmental model might be appropriate. As another example, if the problem situation is ongoing (e.g., scheduling and allocation of resources for orbiter maintenance), then a decision support system, which allows for collection of data to continually update a data base, may be an appropriate approach.

## 6. APPLICATIONS AT THE KENNEDY SPACE CENTER

The techniques of decision analysis, and related methodologies, can be extremely useful tools to the Industrial Engineering Staff at KSC. Some example applications that come to mind include:

1. Scheduling/allocation of resources for orbiter maintenance and repair.
2. Development of an inventory policy for important spare parts of the orbiter.
3. Investigation of the affects associated with retraining of technicians to allow greater sharing of resources among orbiter bays.
4. Investigation of flow time change as a result of a major change in the orbiter.
5. Investigation of the relationship between resource levels (e.g., number of technicians) and orbiter flow time.

In this section of the report, we will describe four specific applications of some of the techniques discussed earlier to problems arising at the Kennedy Space Center. The emphasis in these applications is on the consideration of probabilistic aspects of the problem, through the use of the Demos software package. A separate report has been submitted on the use of the Demos software package (Evans, 1995).

### Evaluation and Ranking of Phase I Small Business Innovation Research Program Project Proposals

Each year, members of the Industrial Engineering Group at KSC evaluate Phase I Small Business Innovation Research (SBIR) program proposals. As specified in the Phase I Evaluator Handbook, the rankings are accomplished by scoring the proposals in each of four different criteria:

1. Scientific/Technical Merit.
2. Anticipated Commercial Application of the Technology.
3. Qualifications (of the key project personnel).
4. Merit of the Proposed Work Plan.

Each proposal is given a score of 0 to 40 points on the first criterion, 0 to 25 points on the second criterion, 0 to 25 points on the third criterion, and 0 to 10 points on the fourth criterion. The total score for a proposal is the sum of its scores on the four criteria.

The Industrial Engineering Group desired a procedure for scoring that would allow probabilistic inputs for each of the four criteria. For example, an evaluator may be very uncertain about the anticipated commercial applications associated with a particular proposal. He/she may think that the potential might be excellent or might be only fair.

After consultation with the IE Group, it was decided that an approach involving the use of a multiattribute utility function would be appropriate for this application. In addition, it was

determined that expansion of the hierarchy past the four criteria listed above would not be desirable. Hence, since these criteria are somewhat subjective in nature, subjective attributes were used in the evaluation process. These subjective attributes assign numerical ratings to various attribute levels, as follows:

- 10: excellent,
- 8: very good,
- 6: good,
- 4: fair,
- 2: poor,
- 0: very poor.

Intermediate scores were also allowed. For example, a score of 8.5 is one-quarter of the way from "very good" to "excellent."

Also, since the weightings had been established as 40, 25, and 10 points, respectively; and since it was specified that a proposal's total score was to be computed as the sum of its scores on the four criteria, an additive utility function of the following form was chosen for this application:

$$u(x_1, x_2, x_3, x_4) = .4u_1(x_1) + .25u_2(x_2) + .25u_3(x_3) + .1u_4(x_4)$$

where  $u_i(x_i)$  represents the  $i^{\text{th}}$  individual attribute utility function and  $x_i$  is the (possibly probabilistic) score for the  $i^{\text{th}}$  attribute. (See Keeney and Raiffa (1993) for discussion of additive utility functions and individual attribute utility functions).

As noted by Keeney and Raiffa (1993) and others, an additive utility function is very restrictive with respect to the decision maker's preference structure. However, given the restrictions imposed by the Evaluator Handbook (that the total score be the sum of the individual scores), the additive utility function was an appropriate choice.

The utility function approach yielded two important advantages. First, probabilistic (or uncertain) scores could be entered for each of the four criteria. Second, the risk preferences of the evaluators could be explicitly considered. For example, an evaluator may prefer a proposal which has a score of 8 (very good) on technical merit for certain, to a proposal which has a 50% chance of a score of 6 and a 50% chance of a score of 10, even though the expected scores on each proposal are the same.

The individual attribute utility functions were then assessed through an interview process with the staff of the Industrial Engineering Department. This process employed the midvalue splitting technique as described by Keeney and Raiffa (1993). The output from the process was a series of points on the graph of the individual attribute utility functions. The linear interpolation feature of the Demos package was employed to compute the utility function values associated with attribute scores. These coordinates on the graphs are given below:

$x_1$	0	3.1	3.8	4.5	5.3	6.5	7.7	8.8	10
$u_1(x_1)$	0	.25	.375	.5	.625	.75	.875	.9375	1

$x_2$	0	3.7	5.8	6.8	8	9	9.5	10
$u_2(x_2)$	0	.25	.5	.625	.75	.875	.9375	1

$x_3$	0	4.5	5	7	8	10
$u_3(x_3)$	0	.25	.5	.75	.875	1

$x_4$	0	3.4	5.15	6.05	7.25	8.35	9.15	10
$u_4(x_4)$	0	.25	.5	.625	.75	.875	.9375	1

where  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$  refer to the scores attained on the four criteria: Scientific/Technical Merit, Anticipated Commercial Application of the Technology, Qualifications, and Merit of the Proposed Work Plan, respectively.

These utility function values were input to a Demos model for computation of expected utility. The model is currently set up to accept probabilistic (or deterministic) scores for a proposal on each of the four criteria for a particular proposal by a particular evaluator. Specifically, the model accepts parameter values for a triangular distribution over each of the four criteria:

- a: worst possible score
- m: most likely score
- b: best possible score

If the evaluator decided that he/she were certain about a score on a particular proposal for a particular criterion, then the three inputs (a, m, and b) would have the same values. In addition, if an evaluator wished to use a different distribution to represent his/her uncertainty about a proposal's score on a particular criterion, then one of the other standard distribution functions from Demos could be employed with little change to the current model.

Output from the Demos model includes expected weighted utilities over each of the four criteria as well as expected total utility. The Demos diagram for the model is shown in Figure 6.



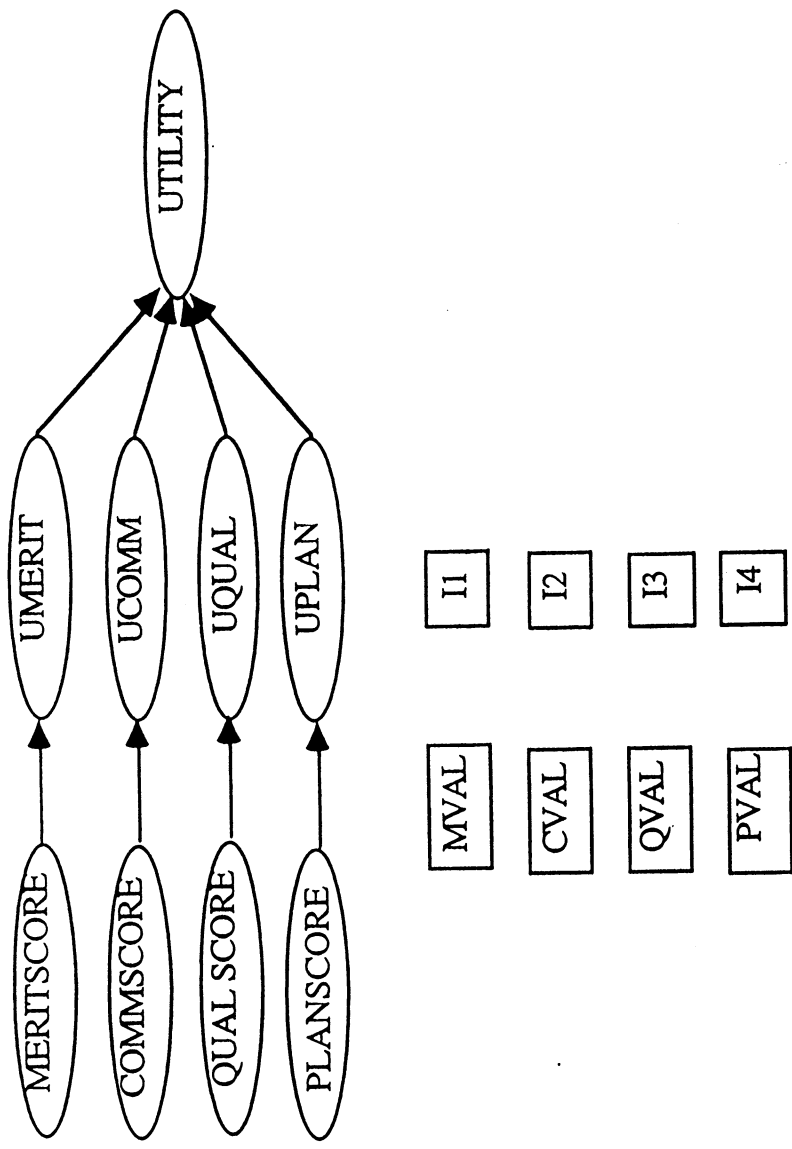


Figure 6. Demos Diagram for the SBIR Proposal Ranking Model.

In this model, the probabilistic scores for the four criteria are input through the appropriate expressions for the nodes MERITSCORE, COMMSCORE, QUALSCORE, and PLANSORE, and respectively. The points on the individual attribute utility function are input through the nodes MVAL, I1, CVAL, I2, QVAL, I3, PVAL, I4.

#### OMS Heater Mod Benefits Analysis

In 1990 a suggestion was made concerning a modification to orbiter processing activities. By incorporating a simple wiring modification to each orbiter, the necessity to remove the 59-63 and 59-64 doors for the Orbiter Maneuvering System (OMS) Pod, Heater checks could be eliminated. Currently, door removal subjects tiles, filler bar, and associated hardware to potential damage. Removals, inspection, reinstallation, and associated PR/DRs (e.g., as a result of TPS repairs) results in several hundred manhours of direct labor effort. In addition, if the doors are removed on the pad, the possibility of impacting the critical path exists, which can result in overtime and other potential costs.

A various of analyses have been performed since 1990. Finally, in 1995 a group from the Industrial Engineering Department at the University of Central Florida submitted a "deterministic" benefits analysis. The KSC Industrial Engineering Department thought that, as a result of the large number of uncertain variables associated with the problem, a probabilistic benefits analysis would be appropriate.

A Demos model was developed to implement this probabilistic benefits analysis. The main output of this analysis is a probability distribution over expected cost savings per year as a result of implementation of the proposed modification. The major sources of uncertainty in the model (represented as random variables in the Demos model) include the following estimates:

1. The number of indirect labor hours required for each hour of direct labor (labeled RATIO in the model).
2. The expected number of door removals per flow (labeled PDRFLOW for door removals on the pad, and NPDRFLOW for door removals not on the pad).
3. The expected number of flows per year (labeled FLOWS).
4. The expected number of direct labor hours required per door removal (labeled PDHOURDR and NPDHOURDR, respectively, for expected pad and non-pad door removals).
5. The expected material cost per door removal (labeled PMCOSTDR and NPMCOSTDR, respectively, for pad and non-pad material costs).

Savings are divided into pad and non-pad savings. The uncertainty in total savings is a result of the uncertainties associated with the variables listed above.

The diagram corresponding to the Demos model for this application is shown in Figure 7.

An arc pointing from one node to a second node in the diagram indicates a dependence of the second node's variable on the first node's variable. Each node has a specific definition, which defines its relationship to other variables. For example, for the variable NPSA VINGS (expected yearly savings from door removals done off the pad), this definition is given by:

$$\text{NPSA VINGS} = \text{NPDRY} * (\text{NPMCOSTDR} + \text{NPDCOSTDR} + \text{NPICOSTDR})$$

where,

NPDRY = number of non-pad door removals per year.

NPMCOSTDR = material cost per non-pad door removal.

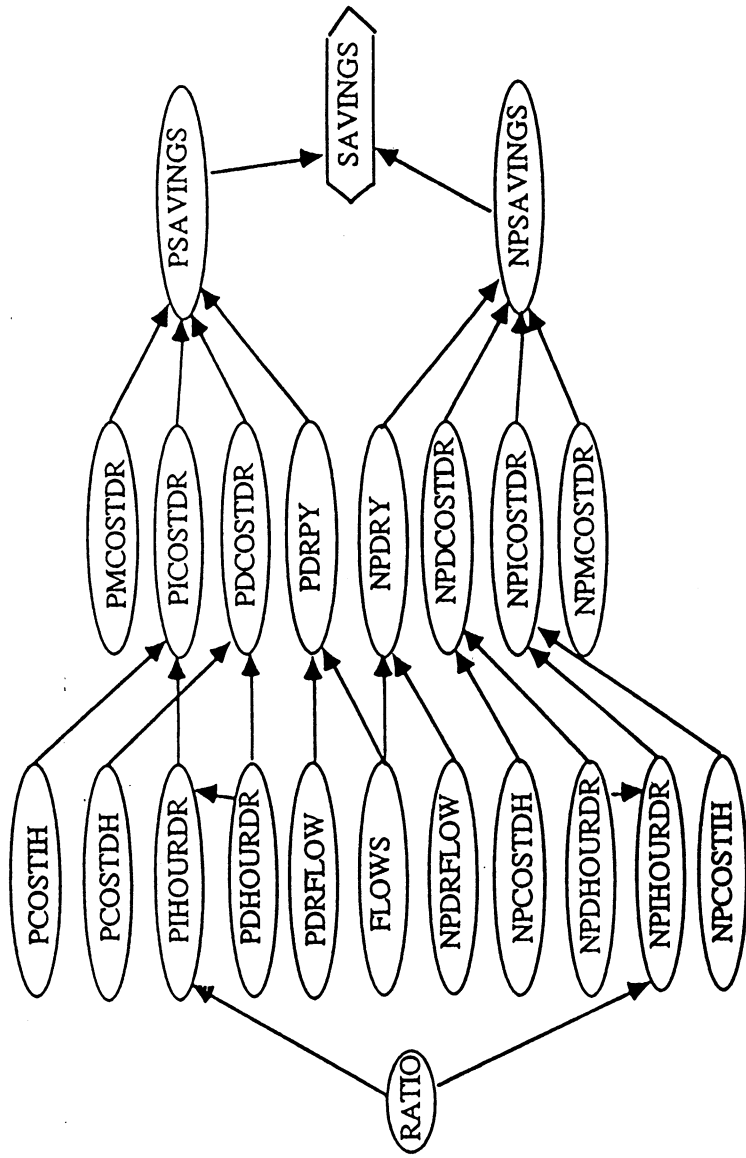


Figure 7. Demos Diagram for the OMS Heater Mod Benefits Analysis Model.

NPDCOSTDR ≡ direct labor cost per non-pad door removal.

NPICOSTDR ≡ indirect labor cost per non-pad door removal.

Other variable definitions in the model are given by:

PCOSTIH (NPCOSTIH) = Pad (non-pad) cost per indirect hour of labor.

PCOSTDH (NPCOSTDH) = Pad (non-pad) cost per direct hour of labor.

PIHOURDR (NPIHOURDR) = Number of indirect hours generated per door removal on the pad (not on the pad).

Assuming the following values of some of the input variables of the model:

1. RATIO is normally distributed with a mean of 4.6 and a standard deviation of 1.
2. FLOWS\* has a value of 6 with a probability of .2, 7 with a probability of .6, and 8 with a probability of .2.

\*Note that, more realistically, since FLOWS is supposed to represent the expected number of flows in a year, it should be modeled as a continuous rather than a discrete random variable.

3. NPDRFLOW is normally distributed with a mean of 4 and a standard deviation of 1.
4. PDRFLOW is normally distributed with a mean of .5 and a standard deviation of .1.
5. PCOSTIH, PCOSTDH, NPCOSTDH, and NPCOSTIH each have values of 40.
6. PDHOURDR and NPDHOURDR are each normally distributed with a mean of 250 and a standard deviation of 50.
7. PMCOSTDR and NPMCOSTDR are each \$5000.

Demos was able to output a sample distribution of expected savings per year resulting from the proposed modification. For example, the expected savings was computed to be at least 2.283 million dollars with a probability of .25, at least 1.84 million dollars with a probability of .5, and at least 1.56 million dollars with a probability of .75.

One advantage of Demos is that the model can be easily, and quickly, changed to allow for alternative assumptions. For example, if the expected number of non-pad door removals per flow were changed from its current value of normally distributed with a mean of 4, standard deviation of 1, to a mean of 1.5, standard deviation of .5, the new probability bands for expected total savings per year would be given by: at least 1.042 million dollars with a probability of .25, at least 840000 dollars with a probability of .5, and at least 597000 dollars with a probability of .75.

Another feature of Demos is its ability to perform an "importance analysis." This allows the model user to understand how much each uncertain input contributes to the uncertainty in the output, by computing the rank order correlation between the sample of output values and the sample for each uncertain input. See pages 4-12 and 4-13 of the Demos User's reference for instructions on how to perform an importance analysis with a Demos model.

#### A General Approach to Assessment of Orbiter Processing Modifications

It was suggested by the personnel of the KSC Processing and Enhancements Division that a Demos model could be developed to assess the value of orbiter processing modifications in general. This section of the report outlines a general Demos model for this type of application.

Processing modifications can generally result in changes relating to four different types of criteria: cost/savings, time, safety, and quality. With respect to safety and quality, certain standards must be met--i.e., if a processing modification does not meet these standards for safety and quality, it will not be considered further. Hence, the problem reduces to the consideration of cost/savings and time.

Costs/savings can be a one-time occurrence (e.g., an initial cost for a modification) or ongoing (e.g., relating to a savings in direct labor hours associated with each orbiter flow). Time refers to an increase/decrease in expected flow time for orbiter processing. A decrease in orbiter flow time will occur only if the relevant activity/group of activities are on the critical path for the

entire flow of activities.

Given these assumptions therefore, a utility function can be used to rank proposed orbiter processing modifications. The utility function would have three attributes:

- $x_1$  = expected yearly cost/savings associated with the proposed modification, in dollars.  
(In this case,  $x_1$  will be positive for a savings, negative for a cost).
- $x_2$  = expected initial cost/savings associated with the proposed modification, in dollars.  
(In this case,  $x_2$  will be positive for a cost, negative for a savings).
- $x_3$  = expected increase/decrease in orbiter processing flow time associated with the proposed modification, in days. (In this case,  $x_3$  will be positive for a decrease, negative for an increase).

In each case, the positive sign was chosen for what would be expected from a modification. That is, one would expect a processing modification to result in a cost savings for each flow, an initial cost, and a decrease (or at least no increase) in flow time.

Typically, one would expect a processing modification to result in some type of change to existing procedures. Therefore, important variables to consider would be:

NOCCPF = the number of occurrences of the change per flow (e.g., the number of times doors were not required to be removed per flow).

DLHOURSOC = the increase/decrease in the number of direct labor hours per . . . occurrence.

MCOSTOC = the increase/decrease in the material cost per occurrence.

FLAWS = the expected number of flows per year.

RATIO = the number of indirect hours required per direct hour of labor.

DLCOST = the cost per hour for direct labor.

ILCOST = the cost per hour for indirect labor.

Note that several of these variables would typically be uncertain quantities, especially NOCCPF, DLHOURSOC, MCOSTOC, and FLOWS.

A Demos model could be employed to compute the expected utility for a proposed modification. The Demos diagram for such a model is shown in Figure 8. In this diagram, the variables, not already defined, are given as:

DLSAVINGS = expected yearly savings in dollars from reduction in direct labor hours.

$$= \text{NOCCPF} * \text{DLHOURSOC} * \text{FLOWS} * \text{DLCOST}$$

ILSAVINGS = expected yearly savings in dollars from reduction in indirect labor hours.

$$= \text{NOCCPF} * \text{DLHOURSOC} * \text{FLOWS} * \text{RATIO} * \text{ILCOST}$$

MCSAVINGS = expected yearly material cost savings in dollars.

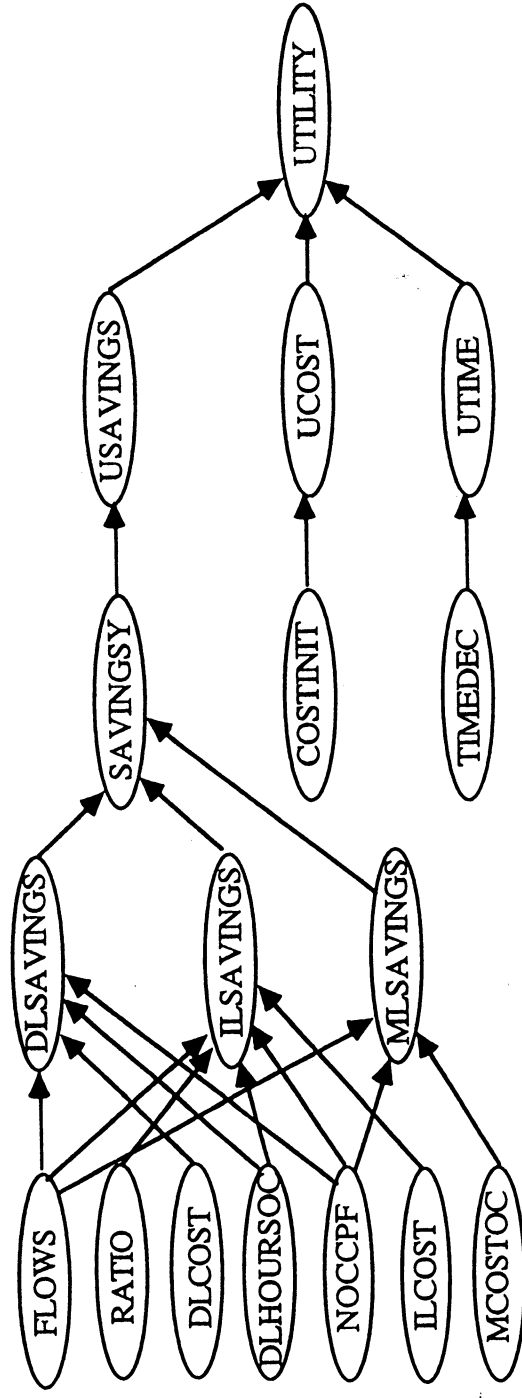


Figure 8. Demos Diagram for Assessment of Orbiter Processing Modifications.

$$= \text{MCOSTOC} * \text{NOCCPF} * \text{FLOWS}$$

SAVINGSY = expected yearly savings, in dollars.

$$= \text{DLSAVINGS} + \text{ILSAVINGS} + \text{MCSAVINGS}$$

COSTINIT = initial expected cost associated with the modification.

TIMEDEC = expected decrease in orbiter flow time, in days as a result of the modification.

Note that the individual attribute utility function values are computed at the nodes with labels USAVINGS, UCOST, and UTIME for the variables  $x_1$ ,  $x_2$ , and  $x_3$ , respectively. The functional values themselves are computed through linear interpolation. The points on the individual attribute utility function graphs are input as values through the nodes labeled SAVINGSVAL and I1 for  $u_1(x_1)$ , COSTVAL and I2 for  $u_2(x_2)$ , and TIMEVAL and I3 for  $u_3(x_3)$ .

Finally, the overall utility function value is computed at the node labeled UTILITY, and is itself a function of the three individual attribute utility functions. A multiplicative form for the utility function was used, as follows:

$$\begin{aligned} u(x_1, x_2, x_3) &= k_1 u_1(x_1) + k_2 u_2(x_2) + k_3 u_3(x_3) \\ &+ k_{12} u_1(x_1) u_2(x_2) + k_{13} u_1(x_1) u_3(x_3) \\ &+ k_{23} u_2(x_2) u_3(x_3) \\ &+ k_{123} u_1(x_1) u_2(x_2) u_3(x_3) \end{aligned}$$

Note that this form can be easily reduced to the additive form by setting all of the scaling constants except for  $k_1$ ,  $k_2$ , and  $k_3$  equal to 0.

#### Choosing Between the NC Machining and The Splash Manufacturing Processes for Orbiter Tiles

After each flight of an orbiter approximately 20 to 100 of the orbiter tiles must be replaced. Two different processes are available for the manufacture of tiles: an NC machining process and a splash process. Individual TPS engineers make the decision as to which process to choose. The decision is currently made based upon the individual engineer's intuition about the cost and time required to manufacture the tile by each type of process.

It was thought by the IE Group at KSC that employing some of the techniques of decision analysis would be helpful to the decision making process. The first step was to understand the process as it occurs now. This was accomplished through interviews with various TPS engineers and through the gathering of data associated with past studies by the IE Group. The results of this data gathering process are illustrated in Figures 9 and 10.

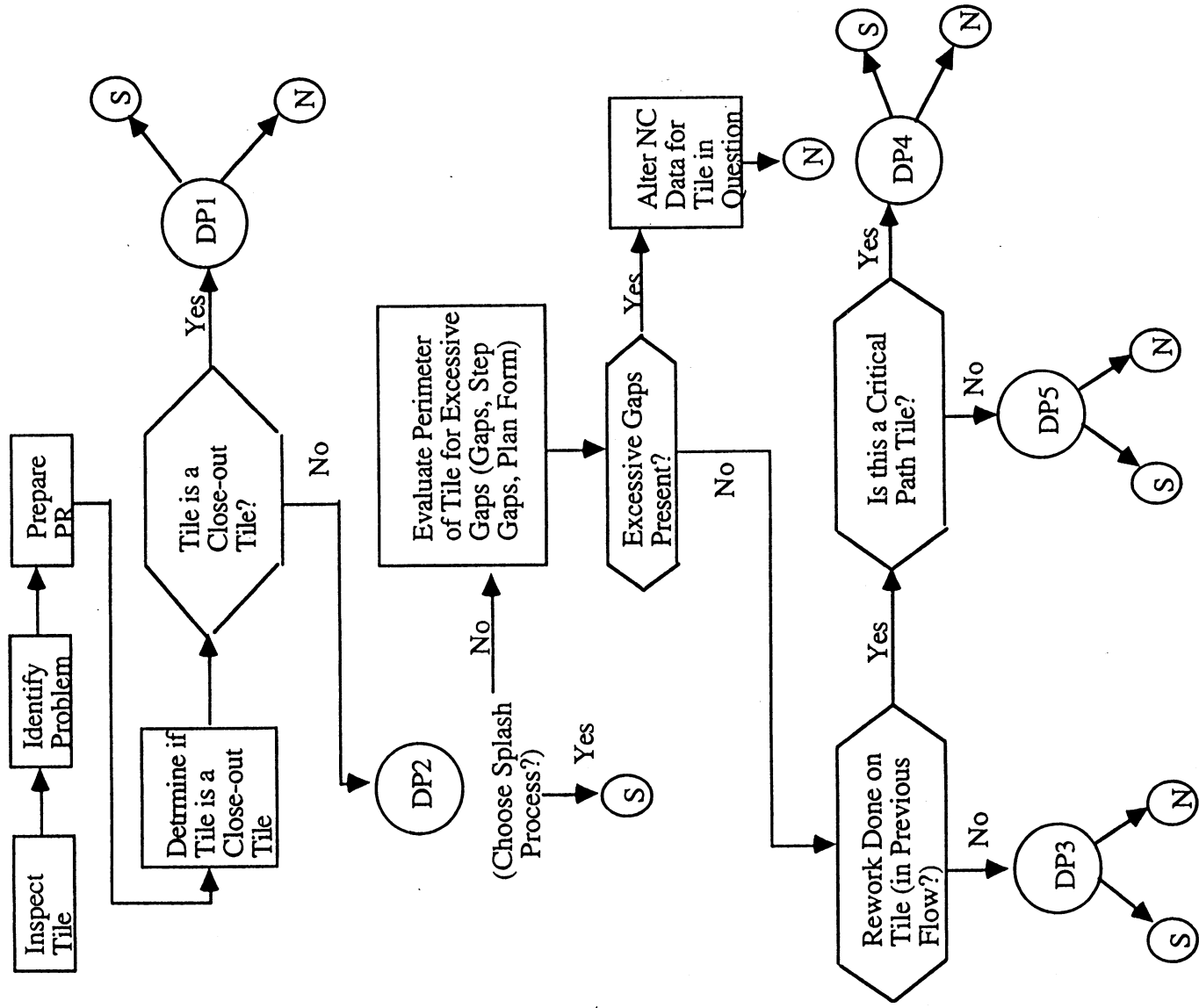


Figure 9. Overall Decision Process for Splash vs. NC Tile Manufacturing Decision.



# NUMERICAL CONTROL TILE PATTERN PROCESS FLOW

M.A. MILLER  
10/13/94

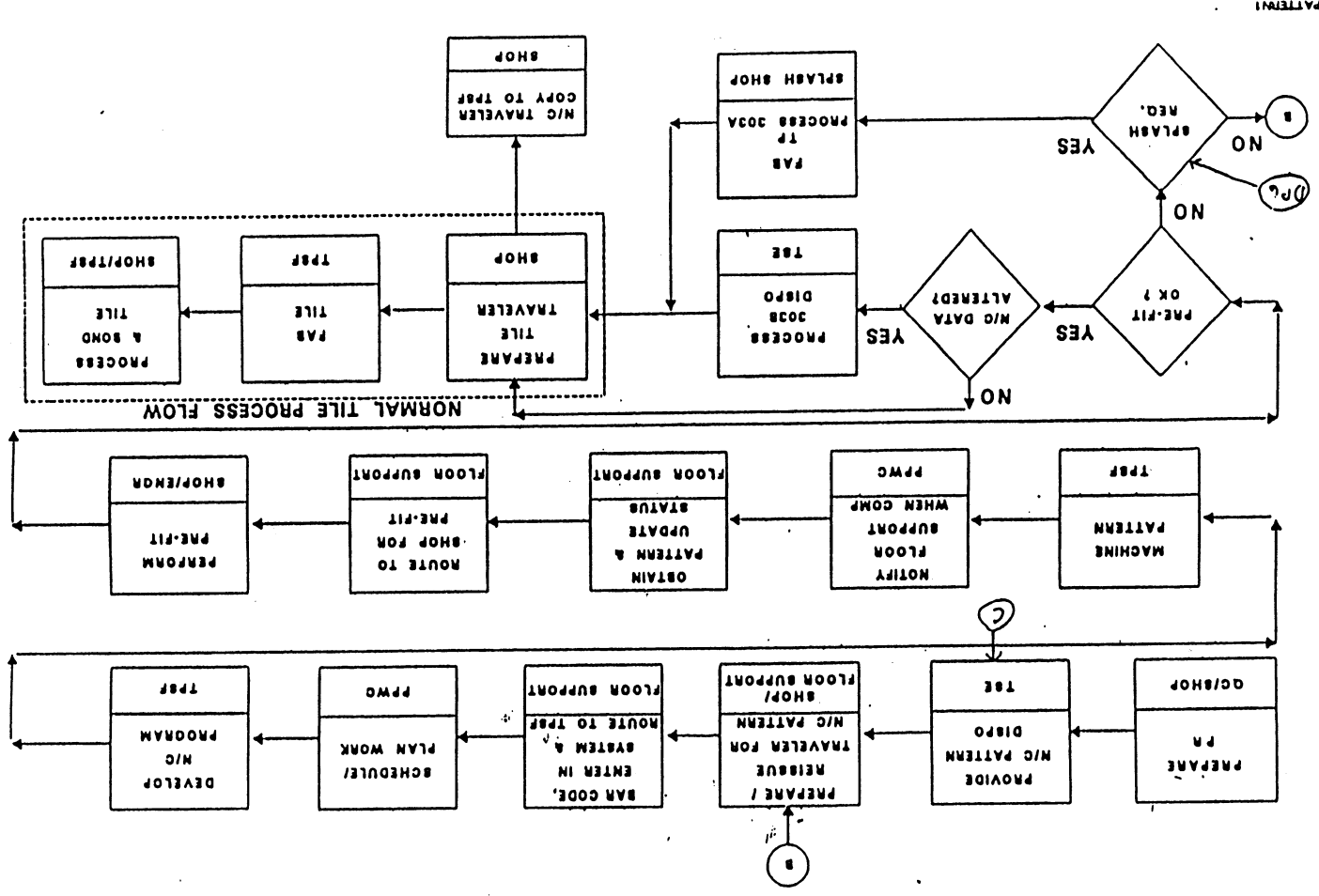


Figure 10. Numerical Control Tile Pattern Process Flow.

The decision as to which manufacturing process to choose can be made at six different points in the overall process, numbered DP1, DP2, ..., DP6 in the relevant Figures. Note that "S" and "N" refer to the splash and NC process, respectively, and note that the last decision point, DP6, occurs after the NC process has been tried at least once. Also, note that the second decision point, DP2, differs from the others in that the decision is to either choose the splash process, or to gather more data by evaluating the perimeter of the tiles.

Each decision point corresponds to a different set of information about the tile in question. For examples, at decision point DP4, one knows that the tile is not a close-out tile, excessive perimeter gaps are not present, rework has been done on the tile in a previous flow, and this is a critical path tile. All of this information can be useful in making the appropriate decision.

For example, by gathering and analyzing data on the time and cost associated with the production of tiles by each manufacturing process, categorized by type of tile (hard, medium, and easy) and by point in the overall process at which the decision is made (DP1 to DP6), one can develop evaluative models giving probabilistic estimates of the time and cost required to manufacture a tile. More specifically, let

$f_i(x,y,z)$  = a density function over the time required to manufacture a tile given that process  $x$  is chosen, for a tile of type  $y$ , for a decision made at point  $z$  in the overall process.

$f_c(x,y,z)$  = a density function over the cost required to manufacture a tile, for  $x$ ,  $y$ , and  $z$ .

In the above functions

$x = 1$ , for the splash process  
 $2$ , for the NC process

$y = 1$ , for hard  
 $2$ , for medium  
 $3$ , for easy

$z = i$ , for decision point DP $i$  for  $i = 1, 2, \dots, 6$ .

In an ideal situation, one could assess and use the TPS engineer's utility function to allow him to choose the manufacturing process that would maximize his expected utility over time and cost. The expected utility would be computed through the use of three functions: the utility function,  $f$ , and  $f_c$ .

A more likely approach, given that the appropriate data could be collected, would be for the TPS engineer to just use the  $f$ , and  $f_c$  functions as inputs to his decision process. This input could work in the following fashion.

Suppose that the TPS engineer is at decision point DP4 in the decision process, for a "medium" tile. This means that the tile in question is a critical path tile, rework was done or the tile in a previous flow, excessive perimeter gaps are not present, and the tile is not a close-out tile. The data analysis has indicated that tiles of this type require, on average, 20 days to manufacture with a standard deviation of 4 days using the splash process, and 18 days to manufacture with a standard deviation of 6 days using the NC process. The TPS engineer would then choose one of the two processes based upon his time preferences and the amount of risk he would be willing to take.

Note that instead of presenting the information concerning manufacturing time in terms of mean and standard deviation, this information could also be presented in terms of probability bands (e.g., 10% probability of taking longer than 24 days, etc.).

Another approach for modeling this decision process would be to use a decision tree (French, 1986), since what's involved in this situation is a sequence of decisions to be made over time.

At the time of the writing of this report, the appropriate data to perform the types of analyses described here was still in the process of being collected.

## 7. BRIEF SUMMARY

The techniques of decision analysis and related methodologies can be important tools for the Industrial Engineering Staff at the Kennedy Space Center. This report has described how well-structured problems can be constructed from ill-structured problems, and how the various methodologies of decision analysis can be applied in solving well-structured problems. Important problem characteristics which affect the choice of modeling methodologies are also discussed. Finally, specific applications at the Kennedy Space Center are described.

## References

- VanGundy, A.B., Techniques of Structured Problem Solving, 2nd Edition, Van Nostrand Reinhold Co., New York, 1988.
- Miser, H.J. and E.S. Quade (Editors), Handbook of Systems Analysis: Overview of Uses, Applications, and Practice, Elsevier Publishing Co., New York, 1985.
- Ackoff, R.L., Redesigning the Future: A Systems Approach to Societal Problems, John Wiley and Sons, New York, 1974.
- Basadur, M., S. Ellspermann, and G.W. Evans, "A New Methodology for Formulating Ill-Structured Problems," Omega 22, 627-645, 1994.
- Wilson, G., Problem Solving and Decision Making, Kogan Page Limited, London, 1993.
- Schoennauer, A.W.W., Problem Finding and Problem Solving, Nelson-Hall, Chicago, 1981.
- French, S., Decision Theory: An Introduction to the Mathematics of Rationality, John Wiley and Sons, New York, 1986.
- Keeney, R.L. and H. Raiffa, Decisions with Multiple Objectives: Preferences and Value Tradeoffs, Second Edition, Cambridge University Press, New York, 1993.
- Pegden, C.D., R.E. Shannon, and R.P. Sadowski, Introduction to Simulation Using SIMAN, McGraw-Hill, Inc., New York, 1990.
- Law, A.M. and W.D. Kelton, Simulation Modeling and Analysis, Second Edition, McGraw-Hill, New York, 1991.
- Pritsker, A.A.B., Introduction to Simulation and SLAM II, Fourth Edition, John Wiley, New York, 1995.
- Lumina Decision Systems, Inc., Demos User's Reference, published by Lumina Decision Systems, Inc., 1993.
- Linstone, H.A. and M. Turoff (Editors), The Delphi Method: Techniques and Applications, Addison-Wesley, Reading, Mass., 1975.
- Shachter, R.D., "Evaluating Influence Diagrams," Operations Research 34, 871-882, 1986.
- Bunn, D.W., Applied Decision Analysis, McGraw Hill, New York, 1984.

Saaty, T.L., Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex World, Second Edition, University of Pittsburgh, Pittsburgh, PA 1988.

Nemhauser, G.L., Optimization, North Holland, New York, 1989.

Evans, G.W., "Using Demos as a Modeling Tool for Decision Problems," NASA/ASEE Technical Report, Processing and Enhancements Division, Kennedy Space Center, June 1995.