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EVALUATION OF DECISION MODELS FOR ENVIRONMENTAL MANAGEMENT

by

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OTHER VOLUMES IN THIS SERIES

Volume 1, Measuring the Benefits of Clean Air and Water, EPA-230-12-85-019.

This volume is a nontechnical report summarizing recent research for EPA on methods development for better estimates of economic benefits from environmental improvement. The report presents the basic economic concepts and research methods underlying benefits estimation as well as a number of case studies, including several from other volumes of this series. Finally, it offers insights regarding the quantitative benefits of environmental improvement.

Volume 2, Six Studies of Health Benefits from Air Pollution Control, EPA-230-12-85-020.

This volume contains six statistical epidemiology studies. They show that large associations between health and current levels of air pollution are not robust with respect to the statistical model specification either for mortality or morbidity. They also find that significant relationships, mostly small, occasionally appear.

Volume 3, Five Studies on Non-Market Valuation Techniques, EPA-230-12-85-021.

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Volume 4, Measuring the Benefits of Air Quality Changes in the San Francisco Bay Area: Property Value and Contingent Valuation Studies, EPA-230-12-85-022.

This volume replicates a property value study conducted in the Los Angeles Basin for the San Francisco Bay area. A taxonomy series of air quality types and socioeconomic typologies are defined for cities in the area to examine how property values vary with pollution levels. The contingent valuation method surveys individuals, directly asking their willingness to pay for changes in air quality. The survey method yields benefit values that are about half the property value benefits in both the Bay area and Los Angeles.

Volume 5, Measuring Household Soiling Damages from Suspended Particulate: A Methodological Inquiry, EPA 230-12-85-023.

This volume estimates the benefits of reducing particulate matter levels by examining the reduced costs of household cleaning. The analysis considers the reduced frequency of cleaning for households that clean themselves or hire a cleaning service. These estimates were compared with willingness to pay estimates for total elimination of air pollutants in several U.S. cities. The report concludes that the willingness-to-pay approach to estimate particulate-related household soiling damages is not feasible.

Volume 6, The Value of Air Pollution Damages to Agricultural Activities in Southern California, EPA-230-12-85-024.

This volume contains three papers that address the economic implications of air pollution-induced output, input pricing, cropping, and location pattern adjustments for Southern California agriculture. The first paper estimates the economic losses to fourteen highly valued vegetable and field crops due to pollution. The second estimates earnings losses to field workers exposed to oxidants. The last uses an econometric model to measure the reduction of economic surpluses in Southern California due to oxidants.

Volume 7, Methods Development for Assessing Acid Imposition Control Benefits, EPA-230-12-85-025.

This volume suggests types of natural science research that would be most useful to the economist faced with the task of assessing the economic benefits of controlling acid precipitation. Part of the report is devoted to development of a resource allocation process framework for explaining the behavior of ecosystems that can be integrated into a benefit/cost analysis, addressing diversity and stability.

Volume 8, The Benefits of Preserving Visibility in the National Parklands of the Southwest, EPA-230-12-85-026.

This volume examines the willingness-to-pay responses of individuals surveyed in several U.S. cities for visibility improvements or preservation in several National Parks. The respondents were asked to state their willingness to pay in the form of higher utility bills to prevent visibility deterioration. The sampled responses were extrapolated to the entire U.S. to estimate the national benefits of visibility preservation.

Volume 10, Executive Summary, EPA-230-12-85-028.

This volume summarizes the methodological and empirical findings of the series. The consensus of the empirical reports is the benefits of air pollution control appear to be sufficient to warrant current ambient air quality standards. The report indicates the greatest proportion of benefits from control resides, not in health benefits, but in aesthetic improvements, maintenance of the ecosystem for recreation, and the reduction of damages to artifacts and materials.

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ABSTRACT

It is almost a categorical truism that decision problems in the public domain are very complex. They almost universally involve multiple conflicting objectives, nebulous types of nonrepeatable uncertainties, costs and benefits accruing to various individuals, businesses, groups and other organizations--some of these being nonidentifiable at the time of the decision--and effects that linger overtime and reverberate throughout the whole societal super-structure.

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FOR ENVIRONMENTAL MANAGEMENT

by

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1. Introduction

Environmental policy concerns itself with protecting our natural surroundings from damages that generally result from human activity. The problem reduces to: (a) finding the mix and levels of these activities that are consistent with "homeostatic" ecological functioning and society's preferences; (b) achieving these levels; and (c) deciding the appropriate role of government in a market economy.

Economic theory has told us that even an ideal, perfectly competitive market system fails in the presence of externalities, public goods and increasing returns to scale. History has shown that these phenomena do cause trouble in a market-dominated economy. In an effort to achieve some form of socially desirable allocation of resources in the presence of market failure and the absence of a "social welfare index," the government must apparently interfere with private decisions.

The discussion below will center around how the Environmental Protection Agency can use some decision models to complete these tasks. Section 2 contains some abstract discussion of models and a survey of some candidate models for environmental policy, Section 3 describes more fully three models that are thought to have potential for environmental management. The theoretical foundations and operational linkages of these models to the environmental problem are described. Section 4 concludes the paper with some remarks about the interrelationships among the recommended models, the informational requirements of each, the satisfaction of model criteria by each and the areas thought promising for future research.

This paper is a response to a charge to identify models useful for environmental management with a focus on those that allow for the consideration of all tradeoffs.

2. The Use of Models for Environmental Policy

Models are, of course, hypothetical descriptions. Assumptions are made to "freeze" certain aspects of reality so that others may be explored. One set of model criteria that a model-builder may require of a model is:

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- A. Measurability and exactness of fit of variables, parameters and relationships to the elements of the actual problem. This would include considerations such as reflection of the objectives of the DM, the validity of the assumptions and sufficient breadth and depth of the model.
- B.1 Ability of the model to be solved via computational methods.
- B.2 Ability of the model to be tested against observation. Criterion B.1 generally applies to programming problems and other "operations research" type techniques. Criteria B.1 and B.2 generally apply to statistical techniques. They both involve considerations such as ease of data acquisition and ease of computation.
- C. Flexibility of the model to include new aspects and/or feedback from operational experience.

Some additional, EPA-specific criteria may be:

- D. Ease of translation of the model output into operational policy actions.
- E. Adaptability of the model to a social choice situation.
- F. Ability of the model to deal with essential environmental problems of externalities and public goods.

One must make a distinction between the model-builder (analyst) and the decision maker (DM). The analyst's understanding of the problem to be modeled is closely related to the perception and objectives of the DM. However, whether the DM is an individual or an organization, objectives are often not explicitly known and/or not amenable to translation into day-to-day decisions. This makes the job of the analyst considerably more difficult. On the other hand, modeling difficulties arise when the analyst makes assumptions that inadvertently remove the essential parts of a problem and/or "molds" the problem to fit techniques that he is capable of implementing.

The objective of government agencies is most generally to promote the "public interest." EPA is concerned with this in environmental matters, and their efforts include the following activities:

1. Knowing the operational meaning of "environmental."
2. Understanding the physical and biochemical dimensions of the ecosphere.
3. Understanding the relation of the environment to engineering/technological systems and to economic/political/legal systems.

4. Determining socially desirable behavior with respect to the environment.
5. With a knowledge of 1. to 3., translating 4. into policy decisions.

Let us concentrate on the relationship of modelling to activities 2. and 3. The process of understanding the natural laws of the ecosphere usually entails some initial observations (by modeller or previous researchers), some theoretical constructs, and testing of empirical hypotheses through controlled experimentation. Some feedback generally takes place from experimentation to hypothesis to theory. In this manner, models of the ecosphere or smaller ecosystems are created.¹

While the physical and biochemical elements make up the ecosphere, the technological and social systems mentioned in 3. above must be linked to it. Through technology, engineering creates a link between natural processes and their use for human needs. Hence, the interface of technology with the ecosphere must be monitored and understood before it can be controlled or influenced. The general process of observation, hypothesis and experimentation is also followed here. Technological components are appended to natural components in ecological models, creating a more realistic picture of the world.

The relationship of the ecosphere to social systems is more subtle. Whereas the ecosphere has an impact on the social development of societies, the major concern for environmental policy is the effect on the ecosphere of economic, political and legal systems. "These models are less testable by controlled" experimentation than models of nature and technology. The environmental analyst must examine them and determine their applicability to his set of problems. Specific links must be made between the elements of the ecosphere and the elements of these social systems. Much research has gone into establishing these links. For example, there are economic models based on materials flow, environmental input/output and environmental property rights.

One must continually ask whether these linkage models are useful in the completion of activity 4. above. The problem of determining the social desirability of human activities is indeed a complicated one. Most social scientists have abandoned the prospect that society has some global value function or social welfare function that social decisions are aimed at maximizing.

The broadest welfare criterion developed by economists is the "Pareto criterion." According to this, society should reallocate its resources until a reallocation cannot make anyone better off (in his own estimation) and everyone else at least as well off. Being equivalent to a unanimity voting rule, this criterion is difficult to operationalize. In this void, three general approaches have been used to arrive at social decisions: (A) utilizing some lower form of efficiency, such as minimum cost, as a guideline for decisions; (B) voting with some form of majority rule; and (C) executive edict. The dividing line between (B) and (C)

depends on the legal separation of the powers of government entities.

Environmental decisions in the United States must follow one or more of these channels. Due to the failure of the market system to cope with externalities and public goods, alternative (A) cannot be achieved privately. Since socially efficient decisions will differ from those which are privately efficient, the inducement to individuals and organizations to choose socially desirable activities must come from (B) or (C) above. Our purpose is to examine what can be done to make alternative (A) as useful as possible in implementing environmental management through governmental action.

2.A. Levels of Decisionmaking

Consideration of models for environmental decisionmaking necessarily takes us back to the role of government in a predominantly free enterprise system. The market system involves a multitude of private decisions being made according to a heterogeneous set of decision techniques (formal or informal). We assume that government agencies attempt to induce socially desirable behavior while preserving decentralized individual choice. Consequently, we must consider that there are various "levels" of decisions being made.

Different levels can be distinguished by the nature and size of the groups affected by decisions made. Let us assume that the set of all DMs can be partitioned (all-inclusive with disjoint classes) in this way. In reality, decision techniques will generally differ among different levels. For example, legislative bodies may use different techniques than households for making decisions. This introduces considerable difficulty into the task of the model-builder.

If a government agency must correctly guide individual decisions, it must not only know its own objectives and constraints (ultimately, its own model), but it must have ideas (ultimately, models) about how those on each level make decisions. Of course, assuming that each class has a uniform technique is quite a simplification. Individuals on the same level can use different techniques. Attempting to model this situation or attempting to partition DMs by techniques used is possible, but it lacks institutional structure. Hence, the partition discussed above appears preferable.²

In an effort to represent the complex interdependencies of the real world, the model-builder must find or devise functional models for each level as well as specify the interactions among the levels. This appears to be a permanent disability of social decision processes preserving decentralization. Simplification through aggregation may relieve some of the complexity problems but at a further sacrifice of realism. As we shall see below, such are the tradeoffs made by model-builders.

2.B. Paradigms of Decisionmaking

One of the first dimensions in a discussion of decision techniques is to what degree the problem at hand is quantifiable. Environmental

decisionmaking involves both qualitative and quantitative modelling, and a discussion of their similarities and differences may be useful.

in order to use either type of model, one would need a fairly good understanding of the problem. The attempt is made to arrange elements in a logically consistent manner. This, however, is generally the point of departure. Once logically constructed, the qualitative model may yield results that are useful to a DM. This generally is satisfactory when the problem at hand does not require a precise numerical solution,

The next step in quantitative models is to express the elements of the problem as variables (controllable elements), parameters (uncontrollable elements) and interrelationships among them. Mathematics is used as the language of precision. The variables and parameters must be measurable. The interrelationships must be specified by a formal mathematical structure. Assumptions are made to transform real-world problems into numerically solvable ones. The nature of the model will be highly dependent on the criteria that one imposes upon it, if one needs partial numerical justification for a basically qualitative decision, his demands for precision will be less than one who needs an exact numerical solution.

Critics of quantitative modelling often argue that rigid mathematical formulation of many social problems hides more about the problem than it illuminates. Furthermore, they warn that DMs have a tendency to become complacent. Having a numerical solution induces a feeling that the problem has been solved. While these flaws are clearly possible, they are by no means necessary. It is possible for quantitative DMs to put numerical results in the proper perspective.

it is assumed here that quantitative models are generally desirable in environmental decisionmaking. However, environmental decisions involve individual and social values that may not be cardinally measurable. in the following section, we examine some mathematical models that have varying degrees of "usefulness," even if value is only ordinally measurable.

2.B.1 Mathematical Techniques

Decisionmaking can simply be defined as a process by which one (or more) alternative elements is chosen from a set of possible alternatives. The minimum size of an alternative set is two. Even with one "active" alternative, a DM has the option not to choose it.

Fundamental to the decision process is the concept of objective. One must have a reason for solving a decision problem. Objectives can be expressed at various levels of generality, and the degree to which they are useful in actual problems is a function of what other elements are subsumed in them. For example, EPA's objective of protecting the public interest does not precisely guide negotiations with U.S. Steel to control its discharges. Keeney and Raiffa (10) suggest that objectives be broad guidelines and goals be operational objectives. In this section on mathematical models, objectives will be used to mean the latter. We shall return to this question below.

Stating one or more objectives separates the problem at hand from the rest of the decision universe. Once this is done, one must realize what the constraints on the decision variables are. The constraints may be natural, technological and/or institutional and are considered immutable within the confines of the immediate problem. As in the systems approach, one can generalize the decision system to allow fixed elements in the original problem to vary. At each level, some elements or phenomena will constrain choice and these must be precisely specified.

Certain decision criteria may be imposed on the choice variables that are not as fixed as constraints, but do constrain choice. For example, one may insist that a reallocation of resources to meet environmental standards have no effect on the distribution of income. For simplicity, we shall include criteria in the set of constraints. Within the constraints, choices are made that best achieve the objective. It is difficult to imagine a policy problem that cannot (at least conceptually) be translated into one of constrained optimization. When objectives, constraints and criteria can be rigorously specified, we can make use of the optimization paradigm.

2. B. 1. a Optimization Procedures

The techniques discussed in this section all contain measurable variables and parameters, precise mathematical formulations of objectives and constraints, and the behavioral assumption that the objective function is being maximized or minimized subject to the constraints on the variables. The techniques differ according to whether the variables and functions are considered continuous or discrete, whether the functions and choice sets satisfy various mathematical properties, whether time is explicitly incorporated and whether the variables are considered determinate or probabilistic.³

Linear programming (LP) is a technique in which all of the relevant functional relations are assumed linear. LP models generally employ continuous, determinate variables in nonstochastic relationships. One optimizes a linear objective over a constraint set bounded by linear functions.

The attractiveness of LP stems from the ease with which the program can be solved via several variants of the simplex method. Traded off against this is the fact that linear models, though widely used, are fairly gross approximations of actual situations. Broad linear models have been used to characterize the dimensions of the U.S. economy. In some cases they are purely conceptual, and in others they can yield numerical solutions. The models provide some useful insights into the type, direction and degree of the effects various sectors have on each other. Large-scale programming techniques are available (15) for solution of some of these broad models.

Input/output models can be set up in the form of LP problems. Generally, however, they deal with the physical and dollar flows of the outputs of several aggregated industries to the industries themselves (closed system) and to industries and to final demands of consumers (open systems), in the latter, if final demands are known, the system is solved for the amounts of output of each industry that will satisfy industrial and

consumer demands. Although based on restrictive assumptions such as perfect competition, long-run zero pure profits, fixed proportions production technology and constant returns to scale, it is a useful tool for including the productive sector of the economy in policy-related models. Leontief (17) has included an environmental sector.

What is called nonlinear programming (NLP) need not be devoid of linearity. -This model is applicable when at least one of the relationships in a model is represented by a nonlinear function. Functions are generally determinate and relationships nonstochastic. When the constraints are strictly binding (i.e. must hold with equality), classical Lagrangian techniques can generally be used to generate optimal values of the decision variables. When the constraints are inequalities, generalized Lagrangian concepts become relevant. The Kuhn-Tucker first-order conditions generate sets of optimal solutions. Other techniques must be used to generate actual solutions.

With the greater generality of this method come considerable computational difficulties, even with favorable mathematical properties. Quadratic programming is the special case of NLP that is most tractable, as simplex methods can be employed in computation. In other cases, techniques based on gradients (vectors of partial derivatives) are used to grope along "hills" or "valleys" in search of maxima or minima. The process can be long, involved and costly. In employing NLP techniques, the decisionmaker makes the reverse tradeoff of LP. He opts for greater realism at the price of computational difficulty.

Two complications of the above programming formulations involve the introduction of discreteness (integer programming) and probabilities (stochastic or chance - constrained programming). Integer restrictions can occur in otherwise linear and nonlinear problems. Some variables are allowed to take on only the values of 0 and 1, while others may take on any integer values. The 0, 1 variables occur in mutually exclusive decisions where something is done or not. This form of indivisibility can be generalized to the case where the variables may be chosen only in discrete lumps.

Integer linear models with all 0, 1 variables are generally solved through explicit or implicit enumeration. Explicit enumeration involves listing all possible solutions according to whether the variables each take on a value of 0 or 1. For n such variables, there are 2^n possible solutions. The sheer magnitude may be forbidding. Hence, implicit enumeration is attractive. In this method, the constraints are used to eliminate classes of solutions so that the resulting set is manageable.

When integer linear models involve the more general integer variables, a few different solution methods are applicable. The first involves enumeration where the integers are each translated into binary (0,1) language. The second involves solving the problem as if it were a linear program and rounding to the nearest integer solution. The third is called the "branch and bound" procedure and begins with the normal solution of the linear program. This solution will not generally be all integer, but the

optimal objective value is a bound on the all-integer solution. In a decision tree format, the branch process consists of moving along the paths connecting decision nodes for each variable. Once the noninteger value is gotten, the variable is then restricted to be smaller and greater than the next lower and next higher integers respectively. This restricts the feasible set of the LP problem. The process continues until the LP solution generates all integer values. The fourth procedure is similar to the third except that additional constraints called "cutting planes" are derived from the LP simplex tableau, and these constraints do not eliminate any feasible integer variables. This procedure also stops when the LP solution is all integer. The latter three techniques are useful when the linear problem contains both continuous and discrete variables.

The discrete problem becomes more complicated when the program is nonlinear. Solution methods are somewhat analogous to the linear case in that the nonlinear problems may be solved for each set of assumed values of the discrete variables. Generalized solution processes for mixed problems are given in Benders (3) and Geoffrion (6).

A generalization of deterministic programming models to perhaps better reflect real-world phenomena is the introduction of probability. While the optimization format is preserved, the parameters of the problem are taken as random variables. When some or all of the coefficients (formerly constants) vary according to (known) probability distributions, the usual solution procedures are nullified. This problem is categorized as a stochastic or chance-constrained programming problem.

The solution techniques become more complicated and in some cases are nonexistent. One practical technique is to make the problem determinate and use normal programming procedures. This involves choosing particular values of the random variables, the most attractive of which would be their respective means. The problem generated would be a further approximation of the real-world, given that the model itself is an approximation of reality.

When the decision elements are random variables, the programming problems are transformed into maximization or minimization of the expected value of the objective function, subjected to constraints that have some probability of being satisfied. Depending on the nature of the underlying probability distributions and the ultimate mathematical form of the problem, conditions may be generated to yield optimal solutions. Generally, these stochastic problems are nonlinear, even if the related determinate problem is linear. This further complicates the decision process.

We can combine the discussions of decisionmaking at various levels and formation of objectives with that of programming models. This leads to the discussion of multi-level decision techniques and multiple objective functions. The most general form of the multi-level decision problem allows for decisions made at each level to be coordinated or influenced by decisions made at "higher" levels. Higher, in this case, can mean having more general objectives under which the decisions of the lower levels

are subsumed. This framework can neatly characterize the internal workings of an organization such as a corporation or government agency. In the face of public policy problems, it can be used to represent the interactions of some central authority with individual or group DMs. The simplest model is a dual-level scheme which has the central authority and private DMs on the high and low levels respectively.

To make the link with mathematical programming, we assume that we can characterize each DM's choice problem as a numerical optimization problem. We invoke the property of the systems approach that any system can usually be thought of as a part of a more general system, to show how the levels are linked. Recall that each mathematical model includes variables and parameters. The parameters can be considered variables in a more general system while they are fixed in the smaller one.

The essence of the coordination technique is the ability of the higher level to influence the decisions of the lower level through the manipulation of parameters. This manifests itself in two basic forms: directly affecting the choice variables by introducing parameters to which decision variables of the lower system must conform (model coordination) and indirectly causing the DM to choose levels of variables desired by the higher level through the use of incentives (goal coordination).

These techniques are powerful when the decisions of the various agents are linked through some interaction variables. Both effectively "uncouple" the decision problems so that output from the lower level can be aggregated and used in the higher level objective. Although the uncoupling is artificial, it is reconciled as the lower level decisions are forced to conform to overall system constraints. A critical feature is that room is left for some individual choice so that coordination does not become total control. Some central planning procedures follow this general format but leave out the possibility of individual choice.

The actual mathematical coordination methods (15, 8, 33) are becoming more computationally tractable. The overall solution involves the solution of lower-level programming problems under a given set of parameters, the collection and aggregation of these results by the higher level and incorporation of the results into its objective function. Using the results of the lower-level solutions, the central authority finds the optimal value of its objective over its set of coordinating parameters. Of course, the solution of lower and higher-level programming problems depends on the type of model used and the mathematical properties of the relationships included.

Analysis of multiple objective functions also fits nicely into the social policy framework. The objectives of various individuals or interest groups are incorporated into a group or social objective in some manner. The solution of multiple objective problems yields levels of the choice variables assigned to each of the interested parties. The actual solution techniques depend on the mathematical form of the composite objective function and of the constraints that may be imposed. The

mathematical solution proceeds by either assigning weights to the various parties and finding the best feasible value of the objective, or by vector maximization, which searches for the optimal value of each variable iteratively as the values of the other variables are held constant.

When time is an explicit variable in a problem, the need for techniques of dynamic optimization arise. The classical problem in the calculus of variations (CV) is to find the trajectory of a ball from an initial to a terminal location that minimizes the time travel led between points (under frictionless conditions). An essential concept in the CV and optimal control (OC) is that of the functional. A functional is a mapping from a set of functions into real numbers or vectors. An integral is an example of a functional and many CV and OC models contain maximization or minimization of integrals of some value function over time.

The solution of CV problems comes from examining the variation in the integral value as the choice variables are perturbed by small amounts. Setting the first variation (analogous to the first derivative) equal to zero yields what is called Euler's equation. This first-order, partial differential equation may be solved for one or more functions that either maximize or minimize the integral. The sufficiency of these outcomes is either assumed or demonstrated through complicated mathematical manipulations.

OC models attempt to solve basically the same problems as CV, but the techniques can be more sophisticated. Given some integral objective function, the variables in the problem are categorized as state variables, control variables, costate variables and time. For each point in time, the state variables are relevant indicators in the problem while the control variables are elements that can be manipulated through the decision Process. The state variables are related to the control variables and time in a system of differential equations called state equations. The control problem can be characterized as open loop (optimal path depends only on time) or closed loop (optimal path depends on the state variables and time).

Solution of optimal control problems, as developed by Pontryagin (22), involves the creation of a Hamiltonian system (similar to a Lagrangian system) which conceptually yields solvable differential equations. The costate variables are analogous to Lagrangian multipliers applied to state equations. The function that optimizes the objective integral is the solution, and depending on the mathematical properties of the functions may be a unique and/or global optimum.

Both CV and OC techniques allow the imposition of additional constraints. The solution techniques are not altered drastically and basically follow Lagrangian procedures. OC can be generalized through the introduction of probability. Stochastic control involves the inclusion of random variables in the control problem. Adaptive control involves re-evaluation of the problem at certain decision points in the time horizon so that the control variables may be adapted to current conditions.

Dynamic programming (DP) proceeds through discrete time, ostensibly with the objective being optimized at each point in time. A solution to a DP problem is a vector of choice variables for each point in time. The process may be best described on a conceptual decision tree. One must find the set of sequential decisions that maximizes the value of the objective over time. Backward recursion is used to solve the problem; i.e., the best final consequence is chosen and the path back to its associated decision node is found. This occurs recursively until the path is traced back to initial time.

Whereas the characterization of dynamic problems in terms of CV, OC and DP is logically valid, it often happens that unless some restrictive mathematical assumptions are made, the problems become extremely difficult to solve for numerical time paths. Hence, these techniques are often impractical when precise numerical answers are needed. They can provide useful normative insights into how to induce the real-world system to approach some optimal performance.

2. B. 1. b. Game Theory

Game theoretic models are useful when decisionmaking involves some conflict of interest. Most social policy decisions are of this kind, given scarcity. The two simplest forms of games are those of an individual against nature and two individuals against each other. We shall consider only the latter.

Each individual in a two-person game is assumed to have a set of strategies to play against the other. For each pair of strategies played, there is a payoff function that assigns numerical rewards to each player. The reward structure may be such that what one wins the other loses (zero-sum) or that the players share some nonzero reward pie (constant sum). For zero-sum games it was shown by Von Neumann and Morgenstern (32), that if each player chooses the strategy that harms him least given that the other attempts to harm him most, then that strategy pair will result in a solution in pure strategies (determinate game). If a solution does not exist in pure strategies, then the game is generalized by assigning probabilities to the strategies (mixed strategies). The players are assumed to maximize expected value, i.e., the sum of rewards from each strategy weighted by probability of choice. In general, a mixed strategy solution is found through LP techniques.

When the number of interested parties is greater than two, the possibility of coalition-formation exists. Players would join coalitions if the reward they receive in the coalition exceeds the reward from playing alone. Reward value is assigned to coalitions through the creation of a two-person game between a coalition and a coalition of all other players. The payoff to the coalition in the solution to this game is its value. The function that assigns value to coalitions is called the characteristic function.

An imputation vector is a vector of rewards to various players in the game. Two sets of imputations are important. One is the set of

imputations whereby one player cannot be made better off while others remain as well off (set of Pareto optimal imputations). One property of the Pareto set is that for any imputation outside of the set, one can be found in the set to dominate it in the sense of granting a higher reward to at least one player. The other set consists of imputations that are undominated by any imputations outside of the set (the core). The core is a subset of the Pareto set, but may not exist in some games. Clearly, any social DM would want the resolution of the conflict to be in the core of the game.

There are several other sophisticated game theoretic models that we shall ignore here. The rationale for this is that if a situation is not conducive to the structure of games already discussed, then the more sophisticated game models are irrelevant.

2. B. 1. c. Statistical Techniques

Although probability was introduced in some forms of programming problems, the approach is basically different from statistical analysis. Variables here are considered random variables which take on values according to some probability distributions. Probability can be defined in many ways. The classical definition is that of the frequency of correct outcomes as a ratio of total events that could have had correct outcomes. The Bayesian definition is that DMs have prior subjective probability distributions that are changed through learning by observation into posterior distributions. Both techniques have been used in regression analysis.

In its simplest form, regression analysis attempts to establish some fairly precise functional relationships between a set of dependent and a set of independent variables. However, the nature of the relationship depends on type of regression procedure used. The relationship estimated usually satisfies some desirable properties, e.g., minimum variance.

Based on cross-sectional and/or time-series data, the relationship is fitted to the data according to the properties mentioned above.

Regression techniques have become varied and sophisticated. Linear and nonlinear models are now popular as well as those that mix continuous and discrete variables. Techniques are available to solve systems of simultaneous relations and to test and correct for statistical difficulties such as serial correlation. Without getting into the mechanics of regression, we assume here that regression is used to extract "trend" and "deviation from trend" with respect to the variables involved. These are important in computer simulation and/or forecasting.

Computer simulation is generally used for one or more of the following reasons (24): the original technical problem is too difficult to solve, the DM is trying to get insight into a complex real situation, or the DM is solving a problem that does not yet exist in the real world. Computer models are set up and solved numerically with the use of actual and hypothetical data. The relationships involved in the computer model may be gotten from previous data or may be fabricated.

When computer simulation takes place over time it is equivalent to scenario-building. Whereas scenarios are created to guide us in decisions made now that affect us in the future, they are based on assumptions about a myriad of dimensions of the problem and are subject to "catastrophic" occurrences that destroy trend. The danger is that the extrapolation of relationships based on past data may be fairly useless to guide present and future decisions. Arguments in favor of scenario-building is that scenarios put "bounds" around the problem and are better than operating in a vacuum. Hence, these techniques may be useful in policy analysis, though the exact results cannot generally be implemented per se.⁵

Statistical decision theory tends to have more of a Bayesian than classical underpinning. DMs are thought to have value or utility functions over the alternative choices in the model. Risk is introduced by assuming that outcomes happen according to known probability distributions.⁶ The probabilities are often subjective, following the Bayesian tradition. Based on these probabilities and a DM's attitude toward risk, outcomes are generally chosen in an effort to either maximize expected utility or minimize expected loss.

Attitude toward risk is implicit in the shape of the utility or loss function. This follows from the process of determining the probabilities that need to be assigned to some lottery (composite of outcomes, each with an assigned probability) that make the lottery equivalent to some reward gotten from a certain outcome (certainty equivalent).

In an effort to make the value function operational, Von Neumann and Morgenstern (32) developed a set of axioms which imply a value index that is cardinally measurable.

2.B.2 Quasi or Nonmathematical Techniques (Methods of Decisionmaking)

Individuals may simply make decisions according to "gut-feelings" or other nonmathematical, highly subjective methods. The person may, however, attempt to quantify some, but relatively few, of the elements of the decision problem. We shall call this quasi-mathematical decisionmaking.

As Arrow (1) has shown, one of the ways that we can expect a solution to social or group decision problems is to have a dictator. The solution is simply the set of alternatives that is preferred by that single individual. The other method is to have a set of rules which dictate how choices are to be made. In our society, the closest we come to these two are orders from the President and executive agencies under the guidance of the Constitution. Arrow showed that under "reasonable" assumptions about the social choice mechanism, group decisions processes are fraught with difficulties (including the revered majority rule with the paradox of voting). There does not exist a social welfare function to generate socially optimal alternatives. In the absence of such a decision process, we shall discuss four alternatives: voting procedures, delphi processes, survey methods and cost-risk/benefit analysis. Although the former two have rather well-developed mathematical foundations, we shall treat them as nonmathematical for policy purposes.

The essential ingredients of a voting procedure are a group of DMs, a set of rules governing the deliberations, a voting rule, and a set of alternative choices. Although the formal approaches to these problems are varied and sophisticated, we shall treat simple alternatives here. Assuming some status quo institutional structure, the alternatives for group choice will amend the structure by changing previous aspects or filling voids. The DMs can be thought of as representing other DMs and having some composite preference-function of themselves and their constituents. For every issue that comes before the group, they then can have a "position" by which to judge alternative solutions to the issue. If one alternative is reconcilable with their positions (or becomes reconcilable through argument, logrolling, etc.), they may be induced to vote for it. The alternative that receives the most favorable votes, subject to some rule about the minimum percentage of votes necessary, will be chosen.

The alternative chosen is thought to reflect the group's preferences. However, under any voting rule short of unanimity, there are those members who endure a cost of accepting a choice that they voted against. This type of process can be generalized in a game-theoretic sense (Riker (23)) by allowing the members to form coalitions in order to get certain alternatives chosen,

The Delphi process is somewhat different from the voting process. To address some particular problem, a group of "experts" is consulted for their opinions about its solution. The group never meets, and conflicts inherent in personality confrontations are meant to be avoided. The opinions of the experts are compiled and/or synthesized, and the result is sent back to the experts for further opinions. The process is thought to continue and converge to some consensus decision. The process was developed at Rand Corporation and the literature on it has been growing (26).

Survey methods can also be a nonmathematical approach to decision-making although the data can be input into quantitative models and subjected to statistical (inferential) methods. In the case of surveys, those who probably will be affected by the decisions are asked (directly or indirectly) what their preferences or past decisions over the alternatives are. An essential element in the process is the creation of a questionnaire whereby the information received is reliable (consistent and accurate) and useful in the problem solution.

The core of cost/benefit (CB) analysis is the estimation of the bad and good consequences that result from the potential choice of each alternative. We consider this to be a quasi-mathematical technique since all costs and benefits are generally not quantifiable in environment-related decisions. One attempts to quantify, generally in dollar terms, as many aspects of the problem as possible. If one alternative is possible, it will be chosen over not choosing it if the net benefits of choosing it are greater. When many alternatives are considered, they can be ranked according to net benefits. The one(s) with the highest net benefit will be chosen. If the quantifiable dimensions of the problem are considered, then maximizing the expression (Benefits minus Costs) yields the marginal

benefits-equals-marginal-costs-rule necessary for optimal choice. If qualitative dimensions are also included, then a DM can combine the net benefit calculations with other subjective considerations to yield an overall optimal choice. Since many costs and benefits accrue in the future, the traditional method of discounted present value is employed. Anticipated costs and benefits are deflated by discount factors incorporating the time period and a discount rate. The costs and benefits are summed for each alternative, allowing direct comparisons. The discount rate is a function of subjective time preferences and interest rates.

If we weight the future occurrences of costs and benefits by probabilities of their occurring, we effectively transform CB into RB analysis. Expected present value replaces the present value discussed above,

3. Models Recommended for Environmental Management

In terms of the five activities the EPA must perform in pursuit of the public interest (discussed before Section 2.A.), we shall consider management to include the latter three. In fact, we shall take both the ecological and technological systems as given and outside the realm of environmental management.⁷ Hence, we will deal with environmental linkages to the economic/political/legal systems, the determination of social desirability and the translation of these into policy actions. All of these are very strongly related to the EPA-specific model criteria D, E and F of Section 2. We proceed by evaluating the models discussed in Section 2.B. in terms of these activities and criteria.

EPA has the role of representing the environment in the social decisionmaking process. Broadly speaking, social decisionmaking involves the decisions of private individuals and firms as well as those of government. The goals of individuals, firms, and other government agencies affect the functioning of the EPA. Within government, it must reconcile its activities (i.e., those which are not explicitly stated in legislation) with other social objectives. A clear case of this is the energy development vs. environmental degradation dilemma. Coexisting with other governmental entities places certain constraints on EPA activities as does its budget. Having mentioned these intra-governmental concerns, assume that they are resolved via some exogenous mechanism. Although our general modelling techniques could handle such problems, we restrict our scope to intra-EPA problems.

With the help of basic research in and out of EPA, the physical/biochemical systems are being modelled with increasing sophistication. The interface of these models with actual decisionmaking leads into the realm of environmental management. Information from the natural sciences is useful in identifying substances and their concentrations that may have serious, perhaps irreversible, effects on the environment. It also gives clues about how the by-products of human consumption and production interface with natural ecological processes. There is no doubt that this information is necessary for environmental management, but it is clearly not sufficient. One reason is that the models themselves are approximations

and include "error." The other is that natural science information does not include the values and preferences of the people in society. It is the value problem that causes the management problem to be difficult.

In an atomistic market system with no imperfections, decisions made according to self-interest would theoretically lead to the socially efficient allocation of resources. That this is not the case leads to two related problems. One is to determine the socially efficient allocation of resources. The other is that two important sources of market failure, viz. externalities and public goods, fall squarely into the lap of EPA.

It was noted in Section 2.B.2 that the only guaranteed answers to the social choice problem are dictatorship and a set of comprehensive written edicts. There appears to be no way to incorporate the preferences of individuals and groups into a consistent decisionmaking tool (social welfare function). Among other things, we have not devised a way to find the socially preferred state of the environment.

Conceptually, it is possible to formalize the social choice problem with nearly every type of model or method discussed above. The problem of finding a Pareto optimal allocation of resources has been modeled as a vector maximum problem with excess demand and natural resource constraints (2). Institutional constraints can also be added. As we shall see below, multi-level and multi-objective techniques are directly applicable. A game-theoretic model (29) would include coalition formation in the allocation of resources and would be very closely allied to voting models, if not methods. Actual voting (i.e., by referendum of all citizens), cost/benefit, Delphi and survey techniques seem precluded by the sheer "level" of the problem. Explicit introduction of time would involve the dynamic optimization models. Uncertainty can be introduced to make nearly all of the optimization techniques stochastic. Regression appears difficult as it crucially relies on real data, while simulation is possible with its power of fabrication.

The practical difficulties of modelling the social choice problem should be apparent. We can enumerate some in terms of the model criteria discussed at the beginning of Section 2. Measurability and exactness of fit would be incredibly poor as would the ability to be solved and/or tested. The flexibility of the model would be considerable, and it is a social choice model. Externalities and public goods have been incorporated in these models (27, 9), but even with this the translation into policy actions is virtually impossible. Add to this a desire to preserve decentralized decisionmaking as much as possible, and the problem becomes more difficult to solve.

The socially desirable mix and levels of environmental activities are also difficult to achieve because many environmental phenomena are externalities and/or public goods. Externalities are defined as objects or actions that occur as the result of normal economic activity and directly affect the behavior of other economic agents. The latter are assumed to have no direct control over them. Externalities are external to the market

system since, although there is a quantity supplied, there are no supply and demand schedules to generate market prices.

The trouble caused by externalities is that externality producers have no private motivation to take the effects that their activities have on others into account. Depending on whether the externality is beneficial (e.g., a beautiful garden to a passer-by) or detrimental (e.g., SO_2 emissions), the activity-levels associated with the externality are either too low or too high for social efficiency. In effect, the decisions of the recipients are "coupled" with those of producers through the externality. This affects the freedom of choice of the victims and also causes problems in the aggregation of value.

The externalities literature in economics began discussing externalities as a source of breakdown in perfectly competitive markets. Treating them as anomalies, researchers tried to develop nonmarket tools to incorporate them into the market system. Later, the pervasiveness of externalities was realized and their treatment in the literature broadened. The bias remains, however, toward solutions that utilize private decisions as much as possible. The ultimate theoretical result is to get private DMs to choose socially desirable activity levels in the pursuit of their private interests.

The approaches can be broken down into the following, as stated in Muskin and Sorrentino (21):

. . . (a) taxes based on damages produced to induce externality levels consistent with Pareto optimality; (b) definition of property rights or licenses which create ownership of the medium in which externalities are expressed; (c) prices for "artificial" commodities in an extended market system; (d) wealth transfers associated with private bargaining solutions; (e) legal discharge limits with penalties for violation set for a particular space or particular externality producer; and (f) per unit charges based on the social costs of deviations from the limits in (e). These methods are not mutually exclusive. Approach (e) with (f) is a real-world version of (a), the property rights in (b) may be a starting point for (d), and the licenses in (b) may be the artificial commodities in (c).

The economic approaches must be contrasted with the legal imposition of discharge levels and/or control activities. In most cases, these approaches are static and the variables, including externalities, are determinate. Externalities may have aspects of public goods in models and in the real world.

Public goods are defined as those commodities whereby the consumption of any one agent does not detract from the consumption of others. Some essential aspects of the public goods problem are the nature and size of the group "sharing" the goods, the degree of sharing, and the economic rationality of not revealing true preferences for the goods in the hope that others provide them without excluding anyone. Private producers

would not provide the goods under these circumstances and the market fails.

The nature and size of the group sharing the good is one primary element in the theory of clubs (28). Models were developed that theoretically determine the socially optimal amounts of the public goods that should be produced as well as the number of parties that should be allowed in the club. The type of sharing has been the subject of a considerable literature. Samuelson (27) defined a pure public good as one in which everyone who consumes the good consumes the entire amount (e.g., national defense). Mohring and Boyd (20) defined quasi public good as one where each consumer consumes some fraction of the total quantity of goods. The sum of the fractions is greater than one to represent sharing. Finally, Holtermann (9) split public good into the characteristics of availability and utilization and called the composite a mixed public good. Availability is the public aspect and is consumed by all in the relevant group. Utilization is private, excludable and appropriable.

Having resigned ourselves to a lower level problem than the overall social choice problem, we can examine the relationships of the modelling techniques to aspects of the environmental problem.

Mathematical programming techniques are quite useful approximations to real-world environmental problems if variables, objectives and constraints are carefully specified. The optimization paradigm is not an alien behavioral device, and numerical results can guide policy decisions. Depending on the particular problem and the need for accuracy, there is considerable flexibility in being able to use linear, nonlinear, discrete and dynamic formulations. Nearly all of these can include uncertainty through the introduction of random variables. The models are generally flexible, can yield reasonable numerical results (albeit through various approximations) and can be subjected to sensitivity analyses.

The use of programming models has been widespread in the environmental economics literature. Three LP examples are (11, 13, 21). One standard paradigm is to find a mix of pollution control techniques that minimizes the cost of achieving previously chosen environmental standards. These programs generate dual variables or shadow prices of the environmental constraints that can be used as effluent charges.

While game theory yields insight by depicting explicit strategies in conflict-of-interest situations, numerical results for policy purposes generally would be generated through programming techniques. These models are quite flexible.

The dynamic optimization techniques explicitly introduce the time dimension. Nearly all decisions made by the EPA have their most significant effects in the future. The problem of specifying functions in a programming model is complicated by having to specify them over time as well. This allows for more approximation error. Approximation techniques to solve differential equation systems can be more cumbersome than those to solve programming problems. Hence, sheer computational difficulty often

prevents dynamic optimization techniques from being very useful policy tools. As with game theory, however, these models can yield broad insights. Dynamic environmental control models involve both resource use and environmental degradation.

Regression can be useful to test various hypotheses about the effects of environmental decisions. Simulation can be static or dynamic, determinate or stochastic and may include optimization. Due to its flexibility, a carefully done simulation can yield useful policy guidelines through reasonable numerical results.

Voting as a method of environmental management will be ignored hereafter. It is assumed that voting has been done to elect officials who vote on legislation affecting the environment. Delphi and survey techniques can be important in environmental decisionmaking, but we can regard them as sources of input into broader models. For example, Delphi can be used to set standards for toxic substances, while surveys may provide estimates of the value of environmental amenities (4).

The three models/methods that are considered most useful for environmental management are multi-level models, decision theoretic-risk models and cost or risk/benefit methods. We shall discuss them more fully in this order. While the basic theoretical foundations are discussed in some detail, it is the potential for operationality that is crucial,

3.A. Multi-Level Decision Approaches

The multi-level approach to social choice problems was introduced in Section 2.B.1.a. The discussion of "levels" of decisionmaking in Section 2.A. was crudely combined with that of mathematical programming. The purpose of this section is to proceed more deeply into this decision mechanism, thereby exposing its usefulness for environmental decisions.

As stated above, the environmental problem involves a central authority (EPA) and several private DMs (individuals and firms). EPA desires to influence the decisions made by private DMs to guide them toward socially desirable decisions while preserving decentralization. We will assume that the variables, objectives and constraints of the central authority's and the private DMs' problems are quantifiable. The initial discussion will be general. Specific programming considerations will follow.

Let us suppose, then, that we have the following general optimization problem:

$$\begin{array}{ll} \text{maximize} & f(x) \\ \text{XEX} & \\ \text{subject to} & g(x) \geq 0, h(x) = 0 \end{array} \quad (3.1)$$

where x is a vector of general variables taken from some "feasible" set, $X = \{x: x \geq 0\}$, f is a real-valued function and g, h are vectors of r.v. functions $g_j, h_k, j=1, \dots, J, k=1, \dots, K$. Nonnegativity of variables will be assumed throughout.

Suppose also that there are $i=1, \dots, I$ "subsystems," and that the objective function may be written in separable form:

$$f(x) = \sum_{i=1}^I f_i(x). \quad (3.2)$$

If the system were completely decentralized, the constraints could be decomposed into g_1^i, \dots, h_k^i for each i . There would be no problem in using the solutions to the individual problems

$$\begin{aligned} \max_{x_i \in X^i} \quad & f_i(x) \\ \text{St.} \quad & g^i(x) \geq 0, h^i(x) = 0 \end{aligned} \quad (3.3)$$

to get the solution of (3.1).

It is often found, however, that the decision subsystems are not independent. This can be reflected by introducing "interaction" variables, z , into (3.1), which becomes

$$\begin{aligned} \max_{x \in X} \quad & f(x, z) \\ \text{St.} \quad & g(x, z) \geq 0, h(x, z) = 0 \end{aligned} \quad (3.4)$$

initially, let us break (3.4) into two subsystems. The problem becomes

$$\begin{aligned} \max \quad & f(x, z) = f_1(x_1, z_1) + f_2(x_2, z_2) \\ \text{St.} \quad & g^1(x_1, z_1, z_2) \geq 0, h^1(x_1, z_1, z_2) = 0 \end{aligned} \quad (3.5)$$

$$g^2(x_2, z_1, z_2) \geq 0, h^2(x_2, z_1, z_2) = 0$$

where $x = (x_1: x_2)$; $z = (z_1: z_2)$ and $g = (g^1: g^2)$, $h = (h^1: h^2)$.

Although the objective function is expressed in terms of independent functions, the presence of interaction variables in each constraint system causes a coupling. The individual problems are no longer independent.

Essentially, then, in order to preserve the desirable effects of decentralization, something must be done about the coupled subsystems.

A very plausible approach is to convert the problem into a multi-level form, which, through the use of coordinating variables, effects a decomposition of the interdependent constraint systems.

3. A. 1. Model Coordination (Feasible Method)

This "primal" approach actually constrains the interaction variables to be equal to some fixed value. If we let w be this fixed-valued vector, then in (3.4). we stipulate that $z=w$.

Using a two-level system, we can set up the problems of the two levels:

Level 1. Find individual maxima which are aggregated as

$$F(w) = \max_{x \in X} \{f(x, w) \quad (3.6)$$

s. t. $g(x, w) \geq 0, h(x, w) = 0$

(2) Level 2. Find $\max_{w \in W} F(w)$. (3.7)

The coordinating (or fixed interaction) variable w is determined by Level 2 (center). The iterative procedure of solving (3.4) in this form begins with Level 2 giving Level 1 an estimate of w that it thinks will maximize $F(w)$. Taking this w as given, Level 1 solves its problem for x . Level 1 then feeds these values to Level 2 who evaluates $F(w)$ and attempts to find another w . Let $W = \{w: F(w) \text{ exists}\}$,

in the form of (3.5), this accomplishes a decomposition of $g(x, z]$ and $h(x, z)$ into two independent subsystems, each of whose problem now looks like the following:

$$\begin{aligned} \max_{x_i \in X_i} & f_i(x_i, w_i) \\ \text{St.} & g^i(x_i, w_1, w_2) \geq 0 \\ & h^i(x_i, w_1, w_2) = 0. \end{aligned} \quad (3.8)$$

The problem, of course, can be made more general by increasing the number of subsystems. (3.5) can become

$$\begin{aligned} \max_{x_i \in X_i} & f(x, z) = \sum_{i=1}^I f_i(x_i, z_i) \\ \text{St.} & g^i(x_i, z_1^i, \dots, z_l^i) \geq 0 \\ & h^i(x_i, z_1^i, \dots, z_l^i) = 0, \\ & i = 1, \dots, I, \end{aligned} \quad (3.9)$$

where z_j^i is the vector of interaction variables emanating from system i to system j . Also we can generalize, if necessary, to include more than two levels in the problem.

3. A. 2. Goal Coordination (Dual Feasible Method)

Again using the two-level system we can look at another approach to the coupled subsystem problem. This approach essentially severs the ties between the coupled subsystems. If z_i is a potential variable affecting subsystem j , it is conceptually "stopped" and replaced in midstream by W_i , which j receives. The receiving system j treats W_i as if it could determine its desired value.

This cutting procedure implies that $Z_i \neq w_i$ is possible. However, once independent subproblems have been created, to insure that the overall system is optimized, the "interaction balance principle" is invoked. This states that Z_i should equal w_i , and a penalty function based on Lagrange multipliers is introduced to induce such an equality.

The problem is formulated as:

$$\begin{aligned} \max_{(x, z, w)} \quad & \mathbf{f}(x, z, w, \lambda) = f_1(x_1, z_1) + f_2(x_2, z_2) + A'(z-w) \\ \text{so.} \quad & g^1(x_1, z_1, w_2) \geq 0, \quad h^1(x_1, z_1, w_2) = 0 \\ & g^2(x_2, z_2, w_1) \geq 0, \quad h^2(x_2, z_2, w_2) = 0 \end{aligned} \tag{3.10}$$

where λ' is a transposed vector of penalties. The breakdown into two levels is slightly different from above. Define the set K such that the (x, z, w) in it satisfy the constraints in problem (3.10). To let the λ be the only multipliers that the second level is explicitly concerned with, we stipulate that $(x, z, w) \in K$.

(1) Level 1. Find individual maxima that aggregate into

$$F(A) = \max_{(x, z, w) \in K} \mathbf{f}(x, z, w, \lambda) \tag{3.11}$$

(2) Level 2. Find λ such that $z-w$. (3.12)

Level 2 coordinates with values of the penalties. The iterative procedure is analogous to the feasible method, except for the difference in coordinating variables.

Expanding the penalty function we get:

$$A'(z-w) = \lambda_1 (z_1 - w_1) + \lambda_2 (z_2 - w_2) \tag{3.13}$$

The subsystem problems each become:

$$\begin{aligned}
& \max_{x_i, z_i, w_j} && f_i(x_i, z_i) + \lambda_i z_i - \lambda_j w_j \\
& \text{St.} && g^i(x_i, z_i, w_j) \geq 0 \\
& && h^i(x_i, z_i, w_j) = 0 \\
& && i, j = 1, 2, \quad i + j.
\end{aligned} \tag{3.14}$$

This problem can also be generalized to the case of more than two subsystems and more than two levels.

3. A. 3. Underlying Mathematical Structure

As the above discussion has been general, some underlying mathematical structure must be provided. This is usually provided by the use of projection in the primal or feasible method and the use of the generalized Lagrangian in the dual feasible method. The object in each approach is to establish a function for which the variables are solved at the "higher" level and interposed at the "lower" level.

As we have seen above, the primal problem (3.4) can be translated into the dual-level problem (3.6) and (3.7). The center searches for the w^* that maximizes the aggregate private returns. Because of the uncoupling of the private problems, this leads to a maximization of the objectives of each of the private DMs.

Three basic questions must be raised about the practical operation of this approach. The first question is whether the center's and the private DMs' problems can be quantified. In general, this must be answered empirically in any situation. We have assumed quantifiability as a prerequisite to recommending this type of model. The second question is whether the problems have solutions. We have addressed this in general in Section 2.B.1.a., and we can apply that discussion directly to the private DMs' problems (as per (3.8)). The relationship to the center's problem is more subtle.

For each subsystem, let Z^i be the vector of interconnection variables and w^i the vector of values which they are given by the center. $F(w)$ in (3.6) is called the primal function. $F(w)$ is to be maximized over the set W . The center's primal problem is "projected" into w -space from the private DM problems as the latter contribute to $F(w)$ by solving uncoupled problems (3.8) over the x_i . Since $(w=w^1, \dots, w^I)$ and the subsystems are uncoupled, $F(w)$ can be written

$$F(w) = \sum_{i=1}^I F_i(w^i). \tag{3.15}$$

Some results due to Geoffrion (7) establish the efficacy of the projected primal problem. The first set-of results is that problem (3.4) is infeasible when (3.7) is, (\hat{x}, \hat{w}) optimal in (3.4) implies that \hat{w} is optimal in (3.7), and \hat{w} optimal in (3.7) with \hat{x} optimal in (3.6) implies that (\hat{x}, \hat{w})

is optimal for (3.4). The latter two results show the close relationship between the primal problem (3.4) itself and the projected primal problem (3.7). However, solution to (3.7) is conditional on the existence of \hat{x} .

Geoffrion also shows that if X is compact and convex, W is convex and f , g and h are concave, then $F(w)$ is concave.⁸ This result establishes the existence of a solution to the projected primal problem as well as identifying any local maximum (not necessarily unique) as a global maximum.

The dual approach translates problem (3.4) into a two level coordination problem such as (3.10) and (3.11), (3.12). The Lagrangian function of the form

$$L(x, z, w, \lambda) = f(x, z, w) + A'(z, w) \quad (3.16)$$

is used as the basis of the procedure. As noted above, the $(x, z, w) \in K$, which incorporates the private DMS' feasible choice sets. The interaction variables, z , are not fixed at value w by the center. The coordination procedure begins with the central authority proposing a particular λ , which is a penalty vector based on the deviation of z (produced levels) and w (desired levels). The private DMS solve problems (3.14) and send the results to the center. These are aggregated by the center, the compliance between z and w checked and a new λ sent out. This process continues until perfect compliance is achieved and the overall objective is maximized. The latter goal needs some further explanation. We first consider the generalized Lagrangian function, (3.16).

Expression (3.16) is said to have a saddle-point at $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ if:

$$L(x, z, w, \hat{\lambda}) \leq L(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda}) \leq L(\hat{x}, \hat{z}, \hat{w}, \lambda) \quad (3.17)$$

This states that $(\hat{x}, \hat{z}, \hat{w})$ maximizes L while $\hat{\lambda}$ minimizes it.

Kuhn and Tucker (14) gave conditions for the optimization of a generalized Lagrangian function which **are necessary**, and under **correct** convexity **assumptions sufficient**, for $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ to be **an optimum**.⁹ They also proved that $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ is a **saddle-point** of L if $(\hat{x}, \hat{z}, \hat{w})$ maximizes L over K , the constraints hold at $(\hat{x}, \hat{z}, \hat{w})$ and the **scalar product** of the multiplier vector with the constraint vector evaluated at $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ equals **zero**. What we need from this result is that under certain conditions the λ performs the **minimizing function** in the saddle-point **condition**. They also showed that if $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ is a saddle-point for L , then $(\hat{x}, \hat{z}, \hat{w})$ solves the primal problem. We are now ready to define the dual problem.

$F(A)$ in (3.11) is called the dual function, defined over A where $A = \{\lambda: F(\lambda) \text{ exists}\}$. The dual problem is defined as:

$$\min_{\lambda \in \Delta} F(\lambda) \quad (3.18)$$

Three important results adapted from Lasdon (15) are given. The first is that the dual function $F(\lambda) \leq f(x, z)$ for all $(x, z, w) \in K$ and $\lambda \in \Delta$.

The second is that for $(x, z, w) \in K$ and $\lambda \in \Delta$, $(\hat{x}, \hat{z}, \hat{w}, \hat{\lambda})$ is a saddle-point if $(\hat{x}, \hat{z}, \hat{w})$ solves the primal, $\hat{\lambda}$ solves the dual and $f(\hat{x}, \hat{z}, \hat{w}) = F(\hat{\lambda})$. This establishes the dual problem as part of the optimization. The final result is that $F(\lambda)$ is convex over any convex subset of Δ . We hesitate to impose convexity on the set of multipliers as we did with W in the primal approach. The last result establishes the existence and global (not necessarily unique) property of any optimum.

Once established, then, the primal and dual functions are the tools by which the center coordinates the lower level problems.

3. B. Decision Analysis of Risk

In Section 2.B.1.c, we mentioned the bare elements of statistical decision theory. This section will expand on those remarks by explaining how a risk-theoretic analysis of a public policy problem may give insights and results not provided in other approaches. Much of the discussion is from Keeney and Raiffa (10) and references therein.

The social decision problem at the basis of this paper is to find a set of choices that can be deemed desirable in the face of resource scarcity, multiple (sometimes conflicting) objectives and uncertainty. We shall here emphasize the latter two.

The necessity of understanding a problem qualitatively before it is specified quantitatively was mentioned above. In particular, a set of objectives must be identified. Often a hierarchy is formed, and the level of detail with which lower and lower level objectives are specified is a matter of convenience. On the one hand, increased detail may add to the understanding of the problem. On the other, the increasing complexity may confuse the DM to the extent that he loses sight of the overall problem. The correct degree of detail depends on the situation. The lower level objectives must always be consistent with the overall objectives and collectively must "cover" it.

If we consider the choices to be actions, we can characterize the consequences of these actions in terms of the specified objectives. We shall associate with each objective an attribute. A consequence of an action will be a vector of levels of these attributes. We shall henceforth speak of the multiattribute problem. Attributes are called comprehensive if knowing the attribute level is sufficient to know the extent that the objective has been achieved. They are called measurable if one can obtain both probability distributions and preference orderings over their levels. Some desirable properties of attributes are that they be complete (cover all aspects of the problem), operational, decomposable, nonredundant and minimal. Choices over actions are based on preference rankings of the attributes. When exact attributes cannot be found, proxies are sometimes useful.

We shall discuss the multiattribute problem with respect to theoretical characteristics, but the ultimate aim is to stress operational

aspects. In the case of certainty we shall confront the value function. Under uncertainty, utility functions will surface. While the initial discussion is couched in general terms for an individual DM, it will be generalized to some extent to incorporate group decision problems and preferences over time. Justification for recommending this approach is also given.

3. B. 1 Theoretical Considerations

The DM must choose an action, $a \in A$, from the set of possible actions. If we assume a vector of attributes (evaluators), (X_1, \dots, X_n) , their values are denoted as $(x_1, \dots, x_n) \in X$ where X is a set in consequence space.

The procedure for establishing preferences over actions with certain consequences appears to be easier than the uncertain case, though not inordinately so. We shall assume that there is a one-to-one relationship of actions to consequences and shall speak of preferences over consequences. Let R denote the ordering, "preferred or indifferent to." We are looking for a value function, v , such that for consequences x and x' :

$$x R x' \text{ if and only if (iff) } v(x_1, \dots, x_n) \geq v(x_1', \dots, x_n'). \quad (3.19)$$

In general, it would be desirable if

$$v(x_1, \dots, x_n) = f[v_1(x_1), \dots, v_n(x_n)]. \quad (3.20)$$

The Pareto (vector maximum) criterion discussed in Section 2 allows us to partially rank the x with a $v(x)$. We can say that x dominates (D) x' if $x_i \geq x_i'$ for all i and $x_i > x_i'$ for some i . The set of undominated consequences is the Pareto or efficient set. Every DM would want to achieve this set. It can be theoretically achieved by iteratively fixing the levels of all but one attribute and optimizing over the remaining one, or by setting linear weights over the attributes and optimizing the weighted sum. The former technique treats attributes as independent without imposing judgments on their relative importance. The latter imposes an additive structure, and the choice of weights affects the relative importance of the attributes. If a consequence in the Pareto set is found, it will have been biased by the weights chosen.

The specific form of the value function depends on the underlying preference structure over attributes. Important insights may be obtained from information on how a DM is willing to trade off attributes relative to each other. Consider the case of two attributes X_1, X_2 . In general, the rate of substitution between X_1 and X_2 depends on their levels. Suppose, however, that a given amount of X_1 "buys" more X_2 as the level of X_2 increases and a given amount of X_2 buys more X_1 as the level of X_1 increases, independently (corresponding tradeoffs condition). This condition holds iff the value function has an additive form:

$$v(x_1, x_2) = v_1(x_1) + v_2(x_2). \quad (3.21)$$

To generalize to the case of more than two attributes, we must give some additional definitions. We shall concentrate on the case of three attributes in this paper. The essential comparisons are between a particular set of attributes and its complement.

For attributes X_1, X_2, X_3 , we say that (x_1, x_2) is conditional preferred (CP) to (x_1', x_2') given x_3 if $(x_1, x_2, x_3) P (x_1', x_2', x_3)$, where P is translated, "is preferred to." Attributes X_1, X_2 are preferentially independent (PI) of X_3 if the conditional preferences in (X_1, X_2) space given X_3 do not depend on the level X_3 . If each pair of attributes is PI of the third, the attributes are pairwise preferentially independent (PPI). It can be shown that $V(x_1, x_2, x_3)$ is additive iff X_1, X_2, X_3 are PPI. PPI also implies the corresponding tradeoffs condition above. Attributes X_1, \dots, X_n are mutually preferentially independent (MPI) if every subset every subset is PI of its complement. We can have the general additive value function

$$V(x_1, \dots, x_n) = \sum_{i=1}^n v_i(x_i) \quad (3.22)$$

The crucial point here is that if the above conditions hold on the preferences of the DM, then the convenient additive value function may be used.^{10,11}

in the case of uncertainty about which consequences will follow from an act, the above discussion must be altered. Let us assume that we initially have only one attribute Y which takes on various values, y_1, \dots, y_n .¹² Assume also that the DM has ranked these levels such that $y_1 < y_2 < \dots < y_n$. We can generate a lottery by attaching probabilities (assumed known) to the best (y_n) and worst (y_1) levels of the attribute according to the Von Neumann-Morgenstern (32) tradition. Denote this lottery $[y_1, \Pi_1, y_n]$ where Π_1 is the probability of receiving y_n and $1 - \Pi_1$ the probability of receiving y_1 . The DM sets $\Pi_1 = 0$ and $\Pi_n = 1$. We should have that $\Pi_1 < \dots < \Pi_n$, and each Π_i forms a numerical scale for the y_i .¹³ The expected value of the Π_i can be used to numerically scale probability distributions over the y_i . For action a' in the discrete probability case, we have:

$$\bar{\Pi}_i = \sum_{i=1}^n p_i \Pi_i. \quad (3.23)$$

Actual utility functions can be shown to be linear transformations of the Π_i . For our purposes, we shall assume that utility functions are monotonically increasing in levels of the attribute.

if a lottery L has consequences y_1, \dots, y_n with probabilities p_1, \dots, p_n , and we denote the uncertain consequence by \tilde{Y} , then we can define expected consequence as:

$$Y = E(\tilde{Y}) = \sum_{i=1}^n p_i y_i. \quad (3.24)$$

The expected utility of L is:¹⁴

$$E[u(\tilde{y})] = \sum_{i=1}^n p_i u(y_i). \quad (3.25)$$

We define the certainty equivalent (CE) of a lottery L as \hat{y} such that $y \sim L$ (where \sim "is indifferent to") or

$$u(\hat{y}) = E[u(\tilde{y})] \text{ or } \hat{y} = u^{-1}(E[u(\tilde{y})]). \quad (3.26)$$

Two utility functions are called strategically equivalent (SE) if they yield the same ranking over lotteries. It can be shown that strategically equivalent utility functions are linear transformations of each other.

Another important property of utility functions is the implicit attitude toward risk. We shall generally discuss risk aversion here. In nearly all cases, the opposite of the conditions for risk aversion characterize risk proneness. The in-between case is called risk neutrality.

We shall call a DM risk averse if he prefers the expected consequence of a lottery to the lottery itself. For uncertain \tilde{y} , we have that:

$$u[E(\tilde{y})] > E[u(\tilde{y})]. \quad (3.27)$$

This is equivalent to saying that the DM will prefer the mean as the safer bet, that the DM's utility function is concave, and, since the right hand term in (3.27) is the CE, that the latter is less than the expected consequence of L.

The traditional measure of risk aversion is:

$$r(y) = - \frac{u''(y)}{u'(y)} \quad (3.28)$$

where the primes denote derivatives. Two utility functions u_1, u_2 are SE if $r_1(y) = r_2(y)$.

The risk premium (RP) of a lottery is defined as the expected consequence \bar{y} minus the CE,

$$RP(\tilde{y}) = \bar{y} - \hat{y}. \quad (3.29)$$

This is positive if the DM is risk averse, as he prefers the mean consequence to the CE of the lottery. Along with monotonicity and risk aversion, the way in which risk aversion changes with increasing levels of the attribute has implications on the specific form of the utility function.

With uncertainty and multiattributes, we will consider two additional concepts of independence. If X_1, \dots, X_n are n attributes in real

n - space, they are considered additive independent if preferences over lotteries over them depend not on their joint probability distribution but on their marginal ones.¹⁵ What is sometimes called the fundamental result of additive utility theory is that if all attributes are additive independent in the DM's preferences, his utility function is additive. For two attributes, these can be written as either:

$$u(x_1, x_2) = u(x_1, x_2^0) + u(x_1^0, x_2) \quad (3.30)$$

or

$$u(x_1, x_2) = k_1 u_1(x_1) + k_2 u_2(x_2) \quad (3.31)$$

where $u(x_1^0, x_2^0) = 0$, $u(x_1^1, x_2^1) = 1$ for arbitrary (x_1^1, x_2^1) such that $(x_1^1, x_2^0) P (x_1^0, x_2^0)$ and $(x_1^0, x_2^1) P (x_1^0, x_2^0)$; $u_1(x_1)$ is the conditional u function on x_1 , $u_1(x_1^0) = 0$, $u_1(x_1^1) = 1$; $u_2(x_2)$ is the conditional u function on x_2 , $u_2(x_2^0) = 0$, $u_2(x_2^1) = 1$; $k_1 = u(x_1^1, x_2^0)$ and $k_2 = u(x_1^0, x_2^1)$.

If additive independence holds for all n attributes, then the additive utility function may be written:

$$u(x_1, \dots, x_n) = \sum_{i=1}^n k_i u_i(x_i), \quad (3.32)$$

Attribute X_1 is utility independent (UI) of X_2 if the conditional preferences over lotteries on the levels of X_1 do not depend on the particular level of X_2 . This is analogous to preferential independence under certainty. In fact, UI implies PI. X_1 UI X_2 does not necessarily imply the reverse. When the reverse also holds, we call this mutual utility independence (MUI). For n attributes, any subset of attributes is UI of its complement if conditional preferences over lotteries involving changes in the 'initial set do not depend on the actual levels of the complementary attributes.

x_1 UI X_2 iff $u(\cdot, x_2^0) \text{ SE } u(\cdot, x_2)$ for all x_2 , which implies that u can be written:

$$u(x_1, x_2) = g(x_2) + h(x_2)u(x_1, x_2^1) \quad (3.33)$$

where g and h are positive and depend only on x_2 . (3.33) says that the u function for any value x_2 is a positive linear transformation of the u function for any other (or any particular) value x_2 .

If X_1, X_2 are MUI, then the u function is multilinear. It can come in either form:

$$u(x_1, x_2) = u(x_1, x_2^0) + u(x_1^0, x_2) + k u(x_1, x_2^0) u(x_1^0, x_2) \quad (3.34)$$

or

$$u(x_1, x_2) = k_1 u_1(x_1) + k_2 u_2(x_2) + k_{12} u_1(x_1) u_2(x_2) \quad (3.35)$$

where the same conditions that followed equation (3.31) hold, $k_{12} = 1 - k_1 - k_2$,

and $k = k_{12}/k_1k_2$ are additional scaling factors. In (3.34), it can be easily seen that if $k \neq 0$, then u is multiplicative and if $k=0$, u is additive.¹⁶

For three dimensions, if the attributes are UI of their respective complements, then:

$$\begin{aligned}
 u(x_1, x_2, x_3) = & k_1u_1(x_1) + k_2u_2(x_2) + k_3u_3(x_3) + k_{12}k_1k_2u_1(x_1)u_2(x_2) \\
 & + k_{13}k_1k_3u_1(x_1)u_3(x_3) + k_{23}k_2k_3u_2(x_2)u_3(x_3) \\
 & + k_{123}k_1k_2k_3u_1(x_1)u_2(x_2)u_3(x_3). \quad (3.36)
 \end{aligned}$$

The additive and multiplicative forms are again special cases. With the blossoming of (3.36), it should not surprise the reader that we do not go to higher dimensions.

To theoretically relate the previous part of Section 3.B. to social choice, we will discuss how it may be applied to the latter problem. The two basic paradigms involve the (benevolent) dictator and the participatory group.

Consider n attributes and m individuals. Assume that our central DM can assess individual value or utility functions v_j or u_j for all individuals.

Under certainty we are generally looking for:

$$v(x) = v_D[v_1(x), \dots, v_m(x)], \quad (3.37)$$

and under uncertainty:

$$u(x) = u_D[u_1(x), \dots, u_m(x)]. \quad (3.38)$$

v_D and u_D are the central DM's (CDM's) value and utility functions. The CDM must consider tradeoffs over the m individuals while the latter consider tradeoffs over the n attributes. It is assumed here that

$$v(x) = \sum_{j=1}^m \lambda_j [v_j^* v_j(x)] \quad (3.39)$$

and

$$u(x) = \sum_{j=1}^m \lambda_j \cdot u_j^* [v_j(x)] \quad (3.40)$$

where v_j^* , u_j^* are the CDM's feelings about v_j , u_j , the "marginal" v and u functions for j . If the CDM thinks that v_j and u_j are honestly revealed, it can follow that:

$$v_j^*(x) = v_j(x) \quad (3.41)$$

$$u_j^*(x) = u_j(x) \quad (3.42)$$

and that:

$$v(x) = \sum_{j=1}^m A_j \cdot v_j(x) \quad (3.43)$$

$$u(x) = \sum_{j=1}^m A_j U_j(x) \quad (3.44)$$

Consider first the case of certainty. We mentioned in Section 2.B.2. that Arrow (1) showed the conceptual impossibility of a consistent group ordering reflecting individual preferences. Some assumptions will be used to get around the impossibility by ultimately making interpersonal comparisons of utility.

consider v_j, U_j as attributes in the CDM'S decision problem. The following assumptions will be used:

- (A1) Attributes v_j, v_k are PI of their complement, \bar{v}_{jk} .
- (A.2) AIB. If A improves to A' for j, everyone else as well off, then A' P B.
- (A.3) The U_j are AI.
- (A.4) $u_j^* \text{ SE } u_j$ for all j.
- (A.5) U_j is UI of \bar{U}_j for all j implies that:

$$u_D(u_1, \dots, u_j, \dots, u_m) = g_j(\sigma_j) \cdot u_j^* \text{ for all j.}$$
- (A.6) Let consequences x^1, x^2, x^3 be indifferent to everyone but person j. CDM'S preference over lottery $[x^1, p, x^2]$ vs. x^3 is based on his probability estimates and j's utility.
- (A.7) If all j have the same u_j^* , this should be the group u function.
- (AI') U_j, U_k are PI of \bar{U}_{jk} .

It is obvious that while attributes are subsumed, the decision-theoretic notions are being applied to value and utility functions as "person-related" attributes. The first result we can get is that (AI) and (A.2) hold iff

$$v(x) = \sum_{j=1}^m v_j^*[v_j(x)], \quad (3.45)$$

where $0 \leq v_j \leq 1$ and v_j^* is a positive monotonic transformation of v_j for all j. If we let $v_j^* \equiv v_j^*(v_j)$, then (3.45) reduces to a more common additive form which, however, reflects equity comparisons by the CDM.¹⁷

Another result is that (A.3) and (A.4) hold iff (3.44) holds with $0 \leq u_j \leq 1$, the weighted additive utility function.

Assumptions (A.4) and (A.5) for $m \geq 2$ imply that:

$$u_D(u_1, \dots, u_m) = \sum_{j=1}^m \lambda_j u_j(x) + \sum_{k>j} \lambda_{jk} u_j(x) u_k(x) + \dots + \lambda_{12\dots m} u_1(x) \dots u_m(x), \quad (3.46)$$

where $0 \leq u_j \leq 1$, $0 < \lambda_j \leq 1$.

Assumptions (A1) or (A1'), (A.4) and (A.5) imply for $m \geq 3$ that:

$$u_D(u_1, \dots, u_m) = \sum_{j=1}^m \lambda_j u_j(x) + \lambda \sum_{k>j} \lambda_j \lambda_k u_j(x) u_k(x) + \dots + \lambda^{m-1} \lambda_1 \lambda_2 \dots \lambda_m u_1(x) \dots u_m(x), \quad (3.47)$$

where $0 \leq u_j, u_k \leq 1$, $0 < \lambda_j \leq 1$ for all j , $\lambda > -1$. When $\lambda=0$, (3.47) is of additive form. When $\lambda \neq 0$, (3.47) can be transformed into multiplicative form.

Finally, we have that for $m \geq 2$, (A.1) or (A1'), (A.4), (A.5) and (A.7) hold iff u is of the form of (3.44).

3. B. 2. Operational Considerations

It should be obvious to the reader by now that the degree to which preferences of a DM at any level can be reflected in numerical indices is crucially related to what conditions hold on the preferences. The above theoretical discussion shows that the presence of preferential, additive or utility independence simplifies matters to varying degrees. In operational terms, it would be extremely convenient to have simple additive or multiplicative value or utility functions.

When assessing the preferences of actual DMs, the goal is to discern structure and meaning from answers to hypothetical questions. The DM may not know how he actually feels about certain choices and may not have any logical means of comparing choices. In attempting to ascertain preferences in actual practice, a decision analyst should be careful to ask simple questions of the DM and to be sure not to mold the DM's feelings into a 'convenient mathematical form.

An important part of the assessment of preferences is specifying objectives and attributes as well as identifying alternative actions that generate mixes of attributes (i.e., generate consequences). Once these issues have been clarified, the problem remains to rank the alternatives in a consistent manner. The easiest case would contain a finite number of actions with discrete amounts of a single attribute. The DM would be asked to express his feelings by assigning numerical values to the attribute levels. If a continuous value function were required, interpolation and/or extrapolation could be used with some consistency checks on the "gaps" to obtain it.

The introduction of a second attribute complicates the matter. If the corresponding tradeoffs condition holds, then "conjoint scaling" techniques can be used to assess the value of increments in each attribute in terms of the other independently. The same holds true with preferential independence in higher dimensions. The independence conditions allow us to evaluate each attribute separately. There is a strong motivation to choose attributes that are as distinct from each other as possible. On the other hand, if there appears to be a "correct" set of attributes, the gains from transforming one or more to obtain independence may outweigh the loss of correctness.

The assessment of Von Neumann-Morgenstern utilities over (multi-attribute) consequences and lotteries over consequences is a complex undertaking. With appropriate questioning, a DM should be able to make the needed comparisons for few actions and one attribute. The expected utility criterion is a popular and reasonable tool in this case that is helpful in inferring risk aversion. The condition of monotonicity and the behavior of risk aversion as the attribute level increases together imply specific forms of utility functions. If such information is gotten from the DM, then a specific utility function can be assigned to him.

Several reasons for being concerned about utility independence are that it implies convenient utility function forms that simplify assessment and operational verifiability, it is somewhat realistic when used in real-world problems, it is quite amenable to sensitivity analysis, and it allows the DM to decentralize his problem so that sub-DMs may solve parts of it. The multilinear u function that results from UI is more general than the additive one resulting from additive independence. Hence, it is applicable to a greater variety of real-world problems.

3.C. Cost-Risk/Benefit Analysis

The brief discussion of CB and RB analyses in Section 2.B.2 presented the core of the techniques. We need to elaborate on some points and provide a justification for recommending them. For simplicity, we shall only discuss RB analysis as it subsumes CB.

Consider a set of alternative policy actions, $A = \{a_1, \dots, a_n\}$. We assume that all infeasible (in any sense) choices are left out of A . Denote $B(a_i)$ and $C(a_i)$ as the benefit and cost functions defined over the a_i . As noted above, B and C include only the measurable dimensions of the problem. If all benefits and costs accrue in the present for each alternative, then $[B(a_i) - C(a_i)]$ would be used to rank the a_i .¹⁸ This ranking, combined with qualitative considerations, yields the ultimate choice. The simple problem, however, can become complicated.

Let us assume that benefits and costs accrue in the future, as in most environmental policies. $B_t(a_i)$ and $C_t(a_i)$ will denote benefits and costs accruing in period t if alternative a_i is chosen. Future benefits and costs are rarely known with certainty. We can consider the levels of each to be random variables. As with the other methods, if we do not assume that the probability distributions are known, the problem is

intractable. Even when the distributions are known, the expected present value calculation is simpler if we use the expected values of benefits and costs for each t.

Applying the discount factor for discrete t would yield:

$$EPV_i = \sum_{t=1}^T [\bar{B}_t(a_i) - \bar{C}_t(a_i)] (1+r)^{-t} \quad (3.48)$$

and for continuous t would yield:

$$EPV_i = \int_1^T [\bar{B}_t(a_i) - \bar{C}_t(a_i)] e^{-rt} dt \quad (3.49)$$

for all a_i , where \bar{B} , \bar{C} denote expected values. By either method, the a_i can be ranked by EPV_i . The mechanics of RB is essentially characterized by equation (3.48) or (3.49).

While the foregoing mechanism is mathematically simple, actual estimation of the B_t and C_t functions can be very difficult. Estimation of explicit monetary costs is fairly straightforward, although proprietary interests as well as the uncertainty of the future may even interfere with this. Capturing implicit or opportunity costs and aesthetic costs is more difficult. Add to this the problem of deciding at what level to stop adding ripple effects (secondary, tertiary, etc.), and cost estimation begins to be more art and less science.

One might generally state that broadly construed, benefits are avoided costs and vice versa. With respect to the environmental problem, one can speak of the costs of pollution as the benefits of control. It is the estimation of the latter that is of strong current interest.

The pioneering efforts of measuring environmental control benefits include Lave and Seskin (16) for air pollution abatement and Knetch and Davis (12) for recreational uses of the environment. Since much of the "Methods Development" work (4) and Freeman's new book (5) are dedicated to this area, we shall not get into too much detail here.

The problem reverts back to the absence of a social welfare index. Every policy or change in policy would be reflected in a change in the value of the index. Application of the Pareto criterion would always yield desirable changes. However, due to its operational restrictiveness, economists have developed (hypothetical) compensation tests to check the desirability of change. The result is that changes should be made if those who gain (lose) from the change can (cannot) induce through potential monetary payment the losers (gainers) to accept the change (reject the change) for all distributions of wealth. This approach would achieve Pareto optimality if payments were actually made and if the payments could be translated into appropriate individual welfare gains. R/B analysis essentially operationalizes these esoteric welfare notions.

Candidates for less ethereal "gains" and "losses" include economic (i.e., consumers' plus producers) surplus and the related willingness-to-pay measures, as well as property value and income differentials comparing different levels of environmental control.

The operational approaches to obtaining these measures include demand and supply estimation, competitive bidding for scarce resources, and/or surveys. The relative reliabilities of these approaches has been the subject of much discussion (4).

4. Conclusions and Recommendations for Future Research

This paper amounts to a survey of decision models and the recommendation of three specific ones as amenable to environmental management. Our conclusion is that each of the multi-level, risk-theoretic and risk/benefit approaches appear useful for operational purposes. While the first two models appear more desirable, the third method will dominate in the short run.

The most common bond of the three recommended models/method is that they are all prescriptions to deal with the same multiobjective, uncertainty-ridden problem.

The multi-level approach can be used to give a general equilibrium perspective, categorizing DMs by levels with generally different decision techniques. It directly involves specification of objectives and constraints to the point of quantification. Time and uncertainty of parameters can be introduced, but they complicate the programs considerably.

The devices for uncoupling in this approach directly apply to the interactions caused by externalities and public goods. The two coordination mechanisms correspond closely to the EPA problem of deciding whether to advocate direct regulation and/or emissions charges.

Decision analysis emphasizes close analysis of objectives and attributes. While this is necessary for operation of this approach, it can also be fed into the multi-level approach. Perhaps the most important attribute of decision theory is the analysis of the effects on behavioral utility functions of attitudes toward risk and uncertainty. The latter creep into the EPA problem all the way from accumulating information on variables and interrelationships to the results of its policy decisions on all affected agents through space and time. While uncertainty can be included in the above optimization techniques it is almost considered parametric or peripheral.

In this analysis, risk aversion and its behavior can be measured and empirical implications drawn. There is hypothesizing and experimentation with independence of preferences over objectives, time and/or individuals and groups. The results of these studies can be an input into the multi-level approach, much as optimization from multi-level is used in decision analysis (e.g., maximizing expected utility). The explicit

introduction of weights over individuals or groups can spawn careful consideration of equity issues.

implicit in the decision-theoretic approach is the use of some variant of Von Neumann-Morgenstern utility. The restrictive axioms necessary for its use provide fodder for the canon of critics wary of molding real-world problems into convenient mathematical boxes. This approach to the value problem is analogous to Leontief's input/output system. Though based on highly restrictive assumptions, they both provide some mechanism for decisionmaking which is better than ad-hocery.

Risk/benefit analysis incorporates measurement, but not to the level of value or utility functions. Observable data is used whenever possible. Freeman (5) points out that these measures (and their uses) may be inconsistent with generally accepted value theory. R/B usually involves optimization and can incorporate time and uncertain outcomes,

The informational demands of the three approaches strongly influence their usefulness. In general, information theory such as given in Marschak and Radner (18) and "Methods Development" (4, Vol. IV) can broadly guide decisions on the accumulation, processing and value of information. Formally, the theoretical techniques fit easily into the risk-theoretic framework.

Information necessary to operate the above three approaches include data on the variables and functions of the natural environment, the economic/political/legal systems as well as objectives and constraints of EPA and its divisions. The explicit goal of the multi-level approach is to limit the amount of information needed by the center to approximate a general equilibrium solution. This is done through the creation of independence and solution of subproblems by individual agents.

Risk analysis seems to demand considerable information from the heads of social and individual DMS if more careful analysis of objectives and preferences than implicit in the multi-level approach is undertaken. Information about the future is a problem in all three techniques.

Specific recommendations for future research (and accompanying information acquisition) include the precise specification in the multi-level approach of externalities and public goods as interaction variables. Uncoupling techniques can then be used to create independence, thereby making the approach more operational. Solution algorithms must also be researched.

With risk analysis, the priority should be to research the objectives and preferences of EPA itself with further understanding of its effects on individuals and firms. Explicit analysis of the existence and cost of risk aversion in past EPA actions may yield insights for future improvement.

Research into the refinement of risk/benefit analysis may lead

to the application of the other techniques.

This research appears vital. The "environmental problem" will not disappear, and quantification of as much of the problem as is possible can minimize room for guessing. The concluding words of the Nobel speech of Laureate in economic sciences, Herbert Simon), imply that despite problems this research is worthwhile:

With all these qualifications and reservations, we do understand today many of the mechanisms of human rational choice. We do know how the information processing system called Man, faced with complexity beyond his ken, uses his information processing capacities to seek out alternatives, to calculate consequences, to resolve uncertainties and thereby -- sometimes, not always -- to find ways of action that are sufficient unto the day, that satisfice. (30, p.511)

REFERENCES

¹It might be said that the model that survives critical testing effectively becomes the reality of the situation. Two prominent examples are Bohr's model of the atom and Leontief's input/output model of the production sector of the economy. Both impose logical order on real-world phenomena, although one cannot assert unequivocally that they are true. Modelling of ecological processes is becoming a sophisticated tool for environmental analysis. Functional models represent the eco-sphere in policy analysis.

²Examples of decisionmaking at various levels are readily available and the modelling implications fairly apparent. One such example is a bill for a windfall profits tax on price-decontrolled petroleum sales decided upon through a congressional majority-rule voting procedure. This affects the behavior of oil producers and refiners who are thought to be long-term profit maximizers, and oil product consumers who may be firms or individuals. The latter two groups may be considered profit and utility maximizers respectively.

³The usual mathematical properties are convexity of the relevant decision sets and concavity or convexity of the functions. The former means that all linear combinations of all pairs of points in the set are contained in the set. Concavity (convexity) of a function means that the function value of a linear combination of any two points is greater (less) than a linear combination of the function values. Strict convexity assumptions are usually used to guarantee unique, global optima.

⁴A decision tree is generally a dimensionless graph in the form of a network in which there are sequential-decision nodes and consequence nodes.

⁵An example of where simulation can lead is given in the Club of Rome's report (19).

⁶Uncertainty is sometimes said to exist if these probability distributions are not known.

⁷Excluding technological systems is done for simplicity. It is clear that technology must be involved in environmental management. We imply here that technology will be employed based on economic, political or legal incentives.

⁸A set is compact if it is containable in a sphere of finite radius and it contains all points, a sphere around which contains points in and out of the set (boundary points).

⁹We ignore the fact here that since we have equality constraints in (3.16), the problem is considerably easier. Recall that inequality constraints of the private DM problems were suppressed.

¹⁰In this analysis, a "willingness-to-pay" apparatus may be developed as money becomes an attribute and the rates of substitution between money and other attributes are estimated.

¹¹CP establishes independence for a single value of Z , PI extends this over all z , and MPI extends PI over all attribute pairs.

¹²The reader should not confuse this with an n -dimensional vector of attributes.

¹³The implication is that the "intensity of feeling" for the Certain receipt of any y_i is gauged by the necessary probability of winning the highest reward needed to make the certain outcome and the lottery equivalent in the eyes of the DM.

¹⁴The continuous analogs to (3.24) and (3.25) would be defined with an integral and probability density functions replacing summation and discrete probabilities.

¹⁵If the possible consequences were arrayed side-by-side in a matrix, this means that preferences over a row with various probability distributions over the row are independent of all other rows.

¹⁶One might also note that through suitable transformation, (3.34) can be put into multiplicative form.

¹⁷Equity relates to the distribution of wealth in general or the distribution of the "environmental burden" in particular

¹⁸Of course, an alternative method of some repute is the benefit/cost ratio.

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