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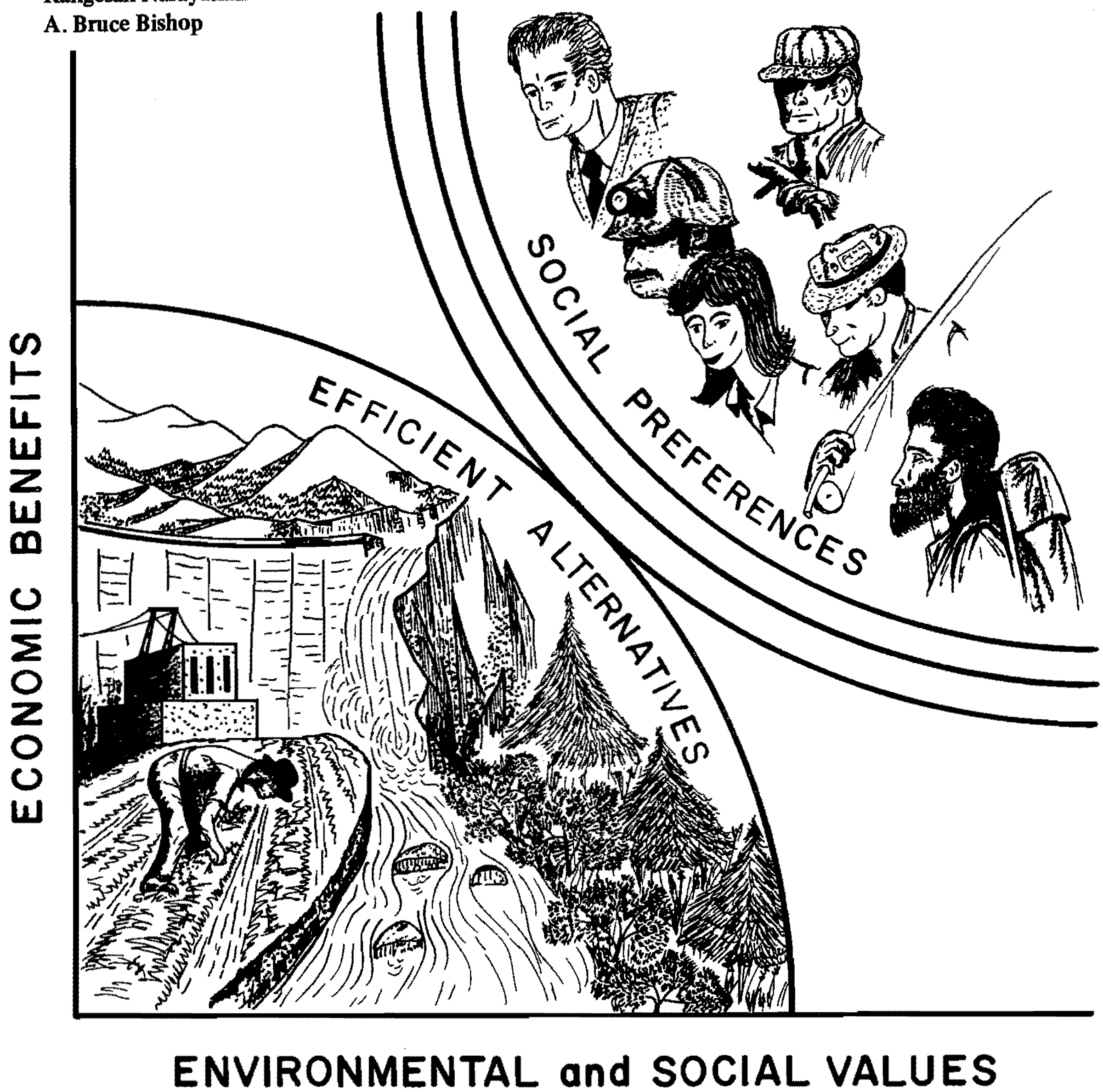

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A METHODOLOGY FOR PUBLIC-PLANNER INTERACTION IN MULTIOBJECTIVE PROJECT PLANNING AND EVALUATION

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ABSTRACT

A review of current multiple objective planning techniques is presented. A critique of certain classes of these techniques is offered, especially in terms of the degree to which they facilitate certain information needs of the planning process. Various tools in operations research are used to construct a new multiple objective planning methodology, called the "Vector Optimization Decision Convergence Algorithm" (VODCA). An application of the methodology pertaining to water resources development in Utah is documented.

Key Words: Water resources planning, multiple objective planning, operations research, planning process, vector optimization, decision making

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TABLE OF CONTENTS

TABLE OF CONTENTS (CONTINUED)

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1.0

INTRODUCTION

1.1 PROBLEM STATEMENT

Planning for water and related land-use programs and projects has often excluded many citizens and interest groups from meaningful participation, thus possibly resulting in plans which are not fully responsive to the needs and wishes of society. This exclusion of viewpoints results both from the noninclusion of potentially interested parties in the planning process and from the inability of techniques used in the planning process to adequately generate and utilize public preference and opinion data. In this regard, the Water Resources Council (1973), in the Principles and Standards, has stated that:

> ...the success of water and related land resources planning depends on meaningful participation of interests concerned with each objective at each step in the planning process. The leaders for water and related land resource planning have the challenging responsibility of achieving such participation while managing effective planning studies and facilitating decision making. This responsibility will require an aggressive program to involve all concerned interests in identifying an area's problems and needs, in planning alternative solutions, and in decisions as to action.

Two concerns are foremost in the design and use of a methodology to incorporate public opinion data in project evaluation. First, criteria should be established for determining what constitutes "useful" public opinion data to be used in the project evaluation and selection stages of the planning process. Only those public participation techniques which generate data which meet these criteria should be used. Second, techniques are required which address the many information management problems that are presently encountered in water resources planning and decision making.

1.2 PURPOSE AND OBJECTIVES OF THE STUDY

Recognizing the need for continually improving interaction between planners, decision makers, and concerned publics in water resources and planning studies, the research reported herein has been aimed at developing tools and procedures which permit citizens and planners to work effectively together in arriving at planning decisions. The objective sought has been to allow planners to better exercise their scientific and professional judgment within the framework of citizens' values during the planning process.

The project has focused on the design and test of a methodology to generate and manage the opinion data necessary to successfully solve what is commonly termed the "vector optimization" (VO) or "multiple objective planning" (MOP) problem. The specific objectives of the study have been to:

1. Research, organize, and classify methods and techniques which are available for use in technical analysis of the physical and operational characteristics of water resources systems.

2. Identify and explore the linkages between methods for operational and technical analysis (Objective 1) and the approaches for assessing or predicting social, economic, and environmental impacts of proposed alternatives.

3. Build on the results of Objectives 1 and 2 to develop tools and procedures for interactive planning including both computer based models and noncomputer techniques. These techniques will be capable of interfacing planners and professional experts with decision makers and public interests in assessment of impacts and evaluation of alternatives in a multiobjective planning content.

4. Apply and test the interactive planning procedure (developed in Objective 3) to a water resource management plan and determine the procedure's effectiveness in improving the joint participation of planners and publics in the planning process.

1.3 CHAPTER INTRODUCTIONS

The materials that follow touch upon a broad range of topics. Chapter 2 presents a review of the water resources planning process, how the MOP problem fits into the process, and a proposed set of criteria or requirements that a successful MOP methodology should fulfill. Chapter 3 contains an overview of the presently available MOP techniques and a brief critique of broad classes of these techniques with regard to the criteria proposed in Chapter 2. Chapter 4 details the development and mathematical basis of the MOP methodology used in this study. The chapter also includes a brief, hypothetical example of the application of the methodology to a simple water resources planning problem. Chapter 5 discusses the application of the methodology to a water resources planning problem in the Uintah Basin of eastern Utah. Finally, Chapter 6 presents a discussion of the results and conclusions of the study.

CHAPTER 2.0

MULTIPLE OBJECTIVES AND THE PLANNING PROCESS

2.1 THE MULTIPLE OBJECTIVE PROBLEM

2.1.1 Introduction

In the past decade, federal legislation, policy, and guidelines have radically expanded the information generation and management responsibilities of natural resources planners and decision makers. At the federal level, planners and decision makers are now obligated to address a wide variety of noncommensurate objectives in the formulation and evaluation of resources development alternatives and in the selection of a preferred alternative. Moreover, the processes by which alternatives are to be formulated, evaluated, and selected are becoming more constrained in terms of the procedures which must be followed and the kinds of information which must be displayed. As a consequence of these factors, the natural resources planner is faced with a number of unfamiliar information management problems, the solutions to which will require the development of new information management and display techniques. This chapter seeks to examine some of the information management problems that resources planners face, especially as these problems are aggravated by the necessity for planning to be done in a multiple objective framework.

2.1.2 The Classical Interpretation of Multiple Objectives

The welfare economics concepts underlying multiple objective analysis have been described by a number of authors (see Cobb 1974; Cohon and Marks 1973; Keith 1974; Major 1969, 1977; Marglin 1967; Bishop et al. 1976a, 1976b; Keeney and Raiffa 1976). The basic conceptual model is shown in Figure 2.1. The two axes measure the contribution of plans to two objectives, national economic development (NED) and environmental quality (EQ), which are noncommensurate. In Figure 2.1, each point on the curve TC, called the production possibilities frontier, represents the net contribution of an alternative to each objective. The curve, TC, represents the boundary of feasible alternatives, with any point lying inside TC feasible but worse than at least one other point lying on TC. For purposes of multiple objective deliberations, all points inside of TC can be ignored. The feasible alternatives which must be considered can be further limited by observing that alternative "a" is preferable to any over the curve "xa," and, similarly, "b" to any over "yb." The points on these curves can also be eliminated from consideration in planning and decision making. The remaining set of alternatives, represented by curve "ab," is known as the noninferior or Pareto optimal set. Any movement along this curve requires a sacrifice of some units of one objective to achieve more of the other.

Selecting an "optimal" alternative from among the points on "ab" requires knowledge of a decision maker's preferences for NED and EQ as described by the indifference curves, IC's, in Figure 2.1. Moving out from the origin, each successive IC represents a higher level of social welfare. The point of tangency, z, of the highest curve, IC_2, with the production possibilities frontier, TC, is the "optimal" or "best compromise solution" (BCS).

The key point of the above discussion is that the planning and decision making process must generate and display two different types of information: 1) technical information describing the set of feasible, noninferior alternatives, and 2) social value and preference information to be used to evaluate trade offs between alternatives and to select an "optimal" alternative.

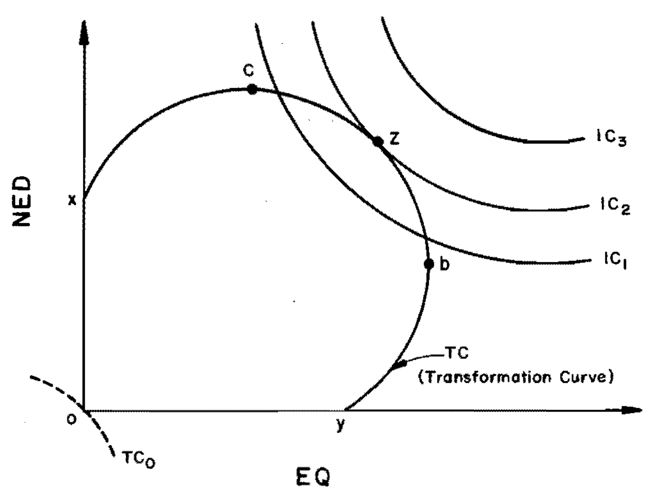


Figure 2.1. Graphical representation of multiple objective planning.

2.2 INFORMATION REQUIREMENTS AND INFORMATION MANAGEMENT PROBLEMS IN THE PLANNING PROCESS

2.2.1 "The" Planning Process

There is no general agreement in the planning community as to what constitutes "the" planning process. There is no unique process; however, over the history of federal management of public natural resources, several agencies have evolved which conduct planning activities with reference to quite specific guidelines and procedures. For example, federal water resources planning activities are governed by the "Principles and Standards" promulgated by the U. S. Water Resources Council (1973). Several authors have commented on the major features of the Principles and Standards (Cobb 1974, Ortolano 1974, Caulfield 1974). Recently, regulations to guide land and resources management planning in the national forest system have been drafted in response to the requirements of the National Forest Management Act of 1976 (U. S. Department of Agriculture 1978). While there is no single, universally recognized process to be followed in resources planning, an examination of the emerging commonalities in the managerial structure and the general procedures of resources planning as identified by a number of authors will reveal a set of information management problems that are more-or-less common to a wide range of resources planners and decision makers.

2.2.1.1 Management Structure of the Planning Process

As discussed above (see also Bishop et al. 1976a, 1976b), one of the major tasks of the planning process is to integrate technical information about the prospective outcomes of alternative plans with value and preference information of interested publics to identify a recommended plan. In interfacing the technical and preference information, the pivotal individual in the planning process is the person designated as the "Lead Planner" in Figure 2.2. According to Caulfield (1974), the objective of the lead planner is to lead the planning exercise in such a way, consistent with public policy impacting him from his superior decision makers, that he will be able to obtain a viable coalition of public support for one of the alternative plans. In other words, the job of the lead planner is to work with his planning staff (to generate technical information about feasible, noninferior alternatives) and with interested publics (to obtain preference and value information) to identify a preferred or "optimal" alternative

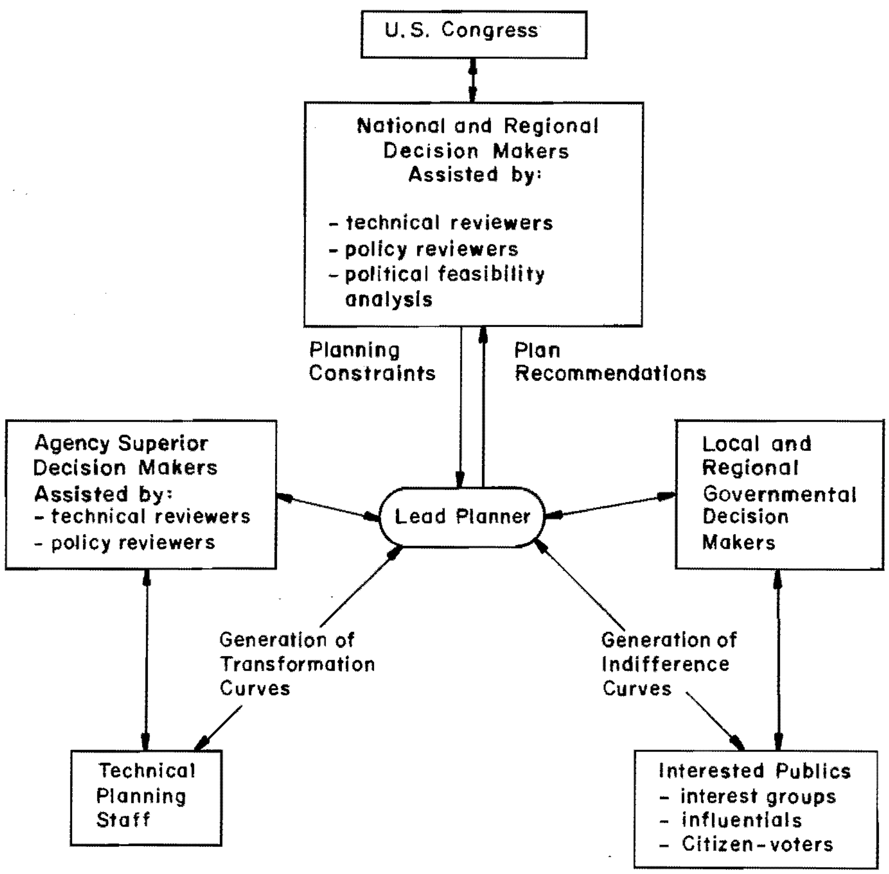


Figure 2.2. Decision maker interaction in the planning process (from Caulfield 1974).

in a way that is consistent with policy, legal, and institutional constraints that are placed on his planning effort.

2.2.1.2 Dynamics and Procedures of the Planning Process

In setting forth procedures for water resources planning, the Water Resources Council (1973) recognized the planning process as a series of steps or tasks which are iterated (Cobb 1974) until a final plan is selected and recommended (see Figure 2.3). The planning process is not viewed (Ortolano 1974) as a linear sequence of activities that can be begun and completed one at a time. Instead, it is seen as a dynamic process wherein activities proceed simultaneously at all times, though at times, certain activities are emphasized or focused on more than others as the process cycles through a number of iterations in moving toward a final decision.

Given the dynamics of the planning process as identified above, the tasks of decision makers, the lead planner, and his planning team might be described as follows (see also Bishop et al. 1976a, 1976b):

1. Relate with publics in defining resources management problems, issues, concerns, and goals.

2. Describe the planning problem and identify the decision variables.

3. Establish resource limits.

4. Construct technical relations among decision variables and resources or standards.

5. Generate the noninferior set of alternatives.

6. Compare alternatives and display trade-offs between alternatives to interested publics.

7. Obtain expressions of preferences for trade-offs from publics.

8. Find compromises through bargaining and negotiation.

9. Select a recommended alternative.

10. Display the decision and the basis for it.

Referring back to Figure 2.1, the main thrust of the planner's efforts is to develop a range of alternative plans that is a good approximation of the noninferior set. The problem of generating these noninferior alternatives has been termed "vector optimization." Mathematically it may be represented as follows:

$$\text{MAX } G(x) = [G_1(x), G_2(x), \ldots G_p(x)] \quad . \; . \quad (2.1)$$

Subject to:

$$f(x) \leq r_i \qquad i = 1, \ldots l \quad . \; . \; . \; . \; . \; . \quad (2.2)$$

$$h_j(x) \geq s_j \qquad j = 1, \ldots m \quad . \; . \; . \; . \; . \; . \quad (2.3)$$

$$x_k \geq 0 \qquad k = 1, \ldots n \quad . \; . \; . \; . \; . \; . \quad (2.4)$$

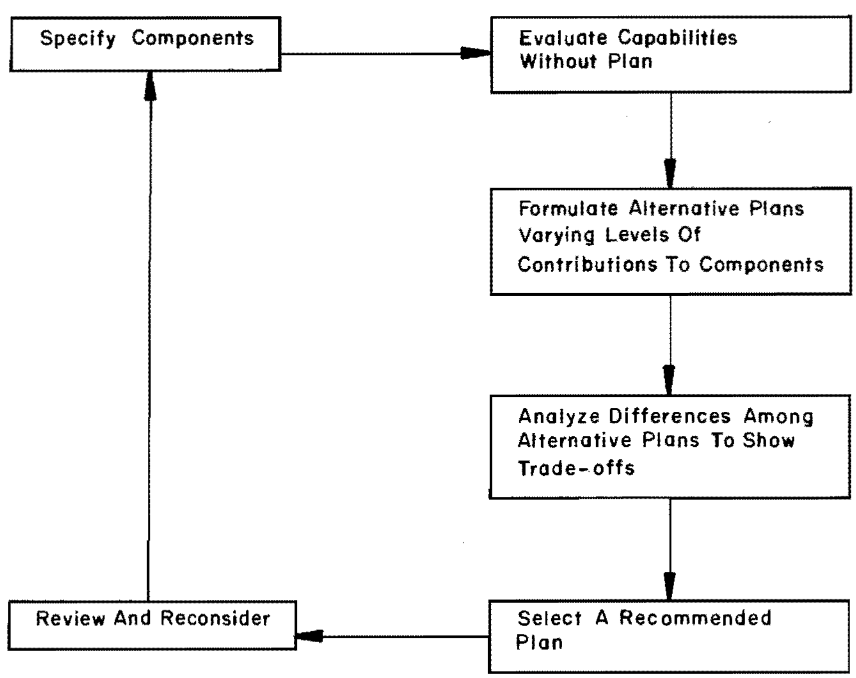


Figure 2.3. Plan formulation.

where $G(x)$ is an objective function of p different objectives, x is a vector of n decision variables; $f_i(x)$ represent constraints imposed by physical and resource limits, r_i; $h_j(x)$ represent constraints set by legal, social or institutional performance levels, standards, or requirements, s_j. The region formed by (2.2), (2.3) and (2.4) is an n-dimensional Euclidean vector space.

With reference to this mathematical representation, the tasks of the planning team might be described as follows:

1. Relate with publics in defining the goal set, G_p.

2. Describe the problem and identify the decision variables, x.

3. Establish resource limits, r_j.

4. Construct technical relations among decision variables and resources or standards, $f_i(x)$, $h_j(x)$.

5. Generate the noninferior set of alternatives, MAX $G(x)$.

Information of the type called for in the above ten steps is the "glue" that binds together the activities in the planning process (Bishop et al. 1976a, 1976b). This is done in two ways: first, each planning activity has associated with it information and data levels that determine the degree of refinement of the task; second, the flow of information between tasks is the basis for reformulating the output of a task in iterating the planning process.

At the same time the technical planning is being accomplished, value information on alternatives is also being generated, refined and ordered by the political decision-making structure in the planning process, a surrogate for generating the indifference curves illustrated in Figure 2.1. Accomplishing this in the plan formulation process involves the following:

1. Identify goals and objectives of all interested publics, G_p.

2. Recognize water resources development policies, standards and constraints, s_j.

3. Determine relevant range of the water resources issue or alternative solution space $\theta_p G_p$, where θ_p is a priority ranking or weightings objectives.

4. Establish where the various interested publics stand within the issue space and what trade offs they might be willing to make, $G^*(a) > G^*(b)$.

The social value portion of the planning process is also an iterative one, with the identification of interested publics and their goals, and determination of the issue space and trade offs preferences dependent upon one another.

The representation of information flow in the planning process, shown in Figure 2.4, relates in a general way how this information and data for deriving public interest decisions on activities, programs, and projects, is generated from the planning process activities. Public input in the form of value information, the top row of boxes in the flow chart, consists of expressions of individual and societal wants, needs, and desires related to aspirations for the future (objectives) and preferences for evaluating resource management options. Correspondingly, planners input technical information, the bottom row, which relates resource availability and capability, alternative actions, and assessment of impacts in order to determine the noninferior set of alternatives considering economic, social, and environmental objectives. The interaction of value information and technical information is brought into final focus through evaluation of the set of alternatives to select a preferred course of action. Finally, with respect to the planning process, the vertical relations indicated the technical and value information correspondence to the tasks within the plan formulation process (Figure 2.3).

2.2.1.3 "The" Planning Process: A Summary

The goal of the planning process is to determine the relative social desirability of proposed resources development alternatives. The process must therefore provide a basis for determining how proposed actions might impact the interests of individuals and groups. It must also provide a means for comparative assessment among alternatives. Its chief purpose is to serve as a value integrating and decision-making activity to focus the interaction of value information and technical information through the evaluation of a set of alternatives. The output of this evaluation is a decision on a preferred course of action and a description of the rationale or basis for that decision.

2.2.2 Information Management Problems in Natural Resources Planning

As indicated in the foregoing sections, the planning process is greatly concerned with the generation, manipulation, and display of a wide variety of data and information. The analysis, dissemination, and evaluation of this information in the planning process pose substantial information management problems to the resources planner (McKee and Crawford 1977, McKee et al. 1978). Two broad types of information management problems can be identified (McKee 1979). These problems have been classed as "information overload" and "information loss."

2.2.2.1 Information Overload

Federal legislation and guidelines (e.g., the National Environmental Policy Act of 1970, the Principles and Standards of the U. S. Water Resources Council, the Forest and

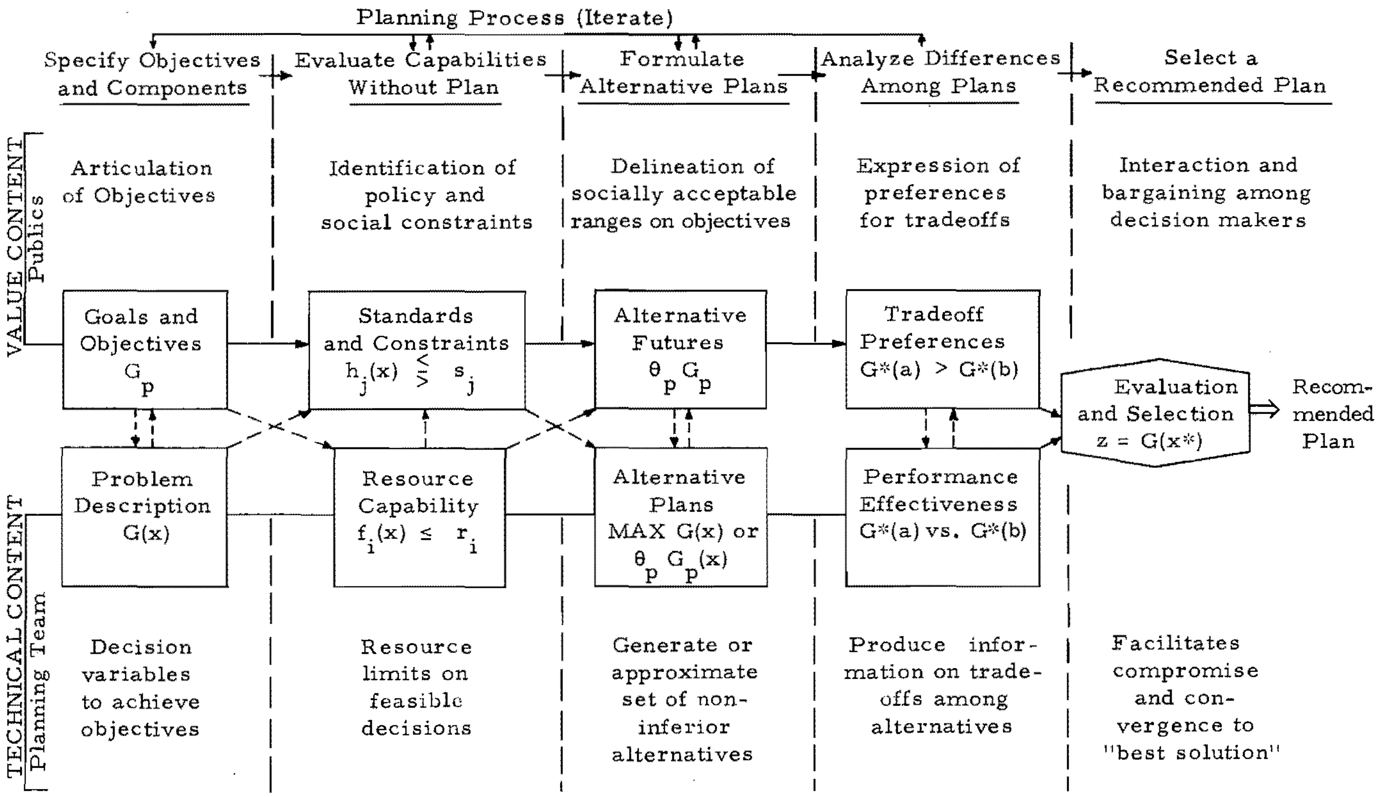


Figure 2.4. A multiobjective planning process.

Rangeland Renewable Resources Planning Act of 1974, the National Forest Management Act of 1976, etc.) have considerably broadened the range of issues which planning efforts must address. Enormous volumes of technical environmental impact information are typically generated for any resources development project that is the least bit controversial. The net result of this information avalanche is that decision makers and interested publics are frequently so deluged with technical data, they would be no worse off if they had much less, and perhaps no information at all. Moreover, the manner in which technical impact information is typically displayed almost prohibits gaining any understanding of the real trade-offs between alternatives.

As a case in point, consider the documentation provided in a draft Forest Service unit plan concerning the impacts of five different alternatives on vegetation type changes and species composition. Table 2.1 presents a compilation of the descriptions of the impacts of the various alternatives on these factors. Two points are to be made here in terms of displaying information about the impacts of alternatives sufficient to provide an understanding of the real trade-offs between alternatives. First, as is normally the case, the descriptions quoted in Table 2.1 were found several pages apart in the draft unit plan. The simple physical location of the descriptions precluded any easy comparison of alternatives and identification of differences and trade-offs. Second, the language used in the descriptions is inexact and does not facilitate the comparison of alternatives. In comparing the phrases "probable increase in fire,..." "some increase in fire,..." "increase in fire,..." and "increase in acreage burned," clear differences, if there are any, between the various alternatives in terms of vegetation type changes do not exactly leap into mind.

Several MOP techniques have been proposed to deal with the information overload problem. Among these are indexing and aggregation methods that collapse complex data sets into less complex sets. These are the so-called "weight-rate-and-calculate" methods. Examples of these include the matrix and linear scoring approaches of Crawford et al. (1973), the Corps of Engineers (1972), Dee et al. (1972), and Leopold et al. (1971). Other methodologies, notably the Techcom methodology proposed by the Technical Committee of the Water Resources Research Centers of the Thirteen Western States (1971, 1974), have more complex indexing schemes. Normally, the procedures followed by these methods require prior assessment of weights and, through various computational processes, reduce the multiple objective problem to a single valued one. These aggregative procedures do not clarify explicit trade-offs, but result in the loss

Table 2.1. An example of how the impacts of resources development alternatives are described.

Factors	Alternatives				
	A	B	C	D	E
Soil and Vegetation					
12.5 Type changes	Probable change in vegetative species composition due to heavier grazing pressure	Probable increase in fire due to heavy recreation use. This will result in type changes in burned timber and also in burned sagebrush lands	Some increase in fire due to increased recreation use. This will result in drastic vegetation changes on burned areas	Increase in fire due to increased recreation use. Type changes will result	Increase in acreage burned
12.6 Altered species composition	Altered species composition on some areas due to long and continued livestock use	Increased vegetation disturbance on developed recreation areas and timber roads--change in vegetation on such site due to planting with introduced species	Increased damage to vegetation from ORV use and vegetative destruction in building new rec. facilities & roads. Vegetation destroyed in these areas will be replaced with introduced grasses & forbs	Vegetative destruction in building new recreation facilities and roads to such facilities. Disturbed areas seeded to introduce species	Some changes in species composition due to increased deer use and decreased cattle use. Probable increase in grass with less forb and production

of planning information rather than the management of it (Bishop et al. 1976a, 1976b).

2.2.2.2 Information Loss and the Decision Gap

The second major information management problem is information loss. Information is lost from the planning process for a variety of reasons, not the least of which is the application of aggregation schemes as discussed above. The major cause of information loss, however, is the organizational structure of the resources planning and decision making process itself (McKee and Crawford 1977, McKee et al. 1978, McKee 1978). The planning and decision making process is stratified and pyramidal in nature. Forming the base of the pyramid is the lowest stratum consisting of field level planners and technicians. At the apex of the pyramid in the top stratum is the U. S. Congress which appropriates funds for resources development projects. Several layers of planners, decision makers, and agencies exist between these two strata. Two types of decisions are made at the various strata of the pyramid that contribute to loss of information. One deals with how information is passed up the pyramid from stratum to stratum, and the other deals with how natural resources development decisions are made and documented.

2.2.2.3 Small Decision Anarchy

At each stratum of the resources planning and decision pyramid, decisions are made with regard to what information about various development projects should be passed to the next highest stratum, and what information should not. This in effect creates a filtering mechanism wherein information is gradually lost as one goes higher up the pyramid. Computerized retrieval and display systems have been proposed (see Roefs 1974) as one means of countering this information loss problem.

2.2.2.4 Big Decision Tyranny

The loss of information of the "small decision anarchy" type causes a gap to form between the gathering and assimilation of technical and public opinion data about the various planning alternatives on the one hand, and the actual selection of a preferred alternative on the other. The factors and decision criteria that are finally considered in decision making and the importance attached to various trade-offs between alternatives are usually not clearly disclosed by decision makers. This creates a "grand canyon" gap that one must leap to get from the technical description of alternatives to the final decision itself. Since reasons and rationale are very seldom provided, it is often difficult to see how the gap was originally crossed by the decision maker.

2.3 REQUIREMENTS OF AN MOP METHODOLOGY

The MOP methodology developed and tested in this project rests on three critical assumptions that relate to MOP information management problems and that color the set of general and specific requirements of an MOP methodology that are stated below. These assumptions are:

1. All major public decisions should be based on the importance of differences and trade-offs between alternatives.

2. Ultimately, all decisions about resources management alternatives are subjective and value-laden; they are based on the preferences, opinions, and viewpoints of publics and decision makers regarding the effects of alternatives.

3. The values, opinions, and viewpoints that led to a major decision about the management of public resources should be documented and displayed.

In terms of what should be required of an MOP methodology, the following thoughts seem appropriate in light of the information management problems described above:

1. The method should document (or at least not obscure) the steps followed in the decision process in assessing both technical and opinion data in arriving at a preferred alternative.

2. The method should reflect and explicitly display information about differences and trade-offs between alternatives; it should not obscure these differences and trade-offs.

3. As much as possible, the method should not contribute to the information loss problem; the technical and opinion data used in decision making should be retrievable at any point in the process.

These concerns, together with the management structure and dynamics and procedures of the planning process give rise to the following specific requirements of an MOP methodology (see Bishop et al. 1976a, 1976b). With respect to the technical content of the planning process, the method should: 1) Facilitate the identification of decision variables in relation to objectives; 2) define feasible decisions in relation to resource limits; 3) generate or be capable of addressing the complete set of non-inferior alternatives; 4) describe trade-offs explicitly; and 5) communicate information in a form that facilitates compromise.

With regard to the opinion and value content of the planning process, the method should: 1) Provide a framework for the articulation of objectives; 2) define feasible decisions in terms of policy and social constraints; 3) use preference and value information to define the set of socially desired alternatives; 4) provide a mechanism for publics to express preferences for trade-offs between alternatives; and 5) facilitate decision maker interaction and bargaining in converging to a "best compromise."

CHAPTER 3.0

REVIEW OF AVAILABLE MOP TECHNIQUES

3.1 CLASSIFICATION OF TECHNIQUES

In recent years, a large number of approaches to the solution to the multiple objective planning problem has been proposed. This chapter presents a brief review of several broad classes of MOP techniques. These techniques are evaluated with reference to the MOP methodology requirements from the previous chapter.

For purposes of presentation, the MOP techniques documented in the literature are grouped here into three broad categories: information organizing, alternative generating, and information integrating. The first category assumes all the pertinent information concerning a limited set of alternatives is available _a priori_. The techniques address the problem of organizing the known information and presenting it to the decision makers in a manner which emphasizes trade-offs and facilitates the decision process. The second category, alternative generating techniques, relies upon the pre-existence of an analytic model of the decision problem which contains information on the decision variable restrictions and the objective variables. The methodologies in this category are oriented toward producing noninferior alternatives from the models. The third category of techniques integrates the considerations of classes one and two. These algorithms interact with the decision maker and utilize the information obtained from the interaction to generate "better" alternatives. The technique developed by this study is in this category.

3.1.1 Nonoptimizing, Information Organizing Techniques

Five principal types of techniques have been identified under this general category (Bishop et al. 1976a, 1976b). These are: 1) Visual techniques; 2) rating and ranking methods; 3) matrix and linear scoring methods; 4) trade-off displays and analysis; and 5) goals evaluation techniques.

3.1.1.1 Visual Techniques

Visual techniques, requiring little or no quantitative analysis, have been widely used (see McHarg 1968, Seader 1975, Steinete 1971) in situations where the objectives and constraints have spatial significance. Social and environmental objectives (which in some applications are treated as constraints) are shaded to represent their relative desirability or undesirability on a series of map or matrix overlays (these may also be generated by computer). Putting these together in various combinations then reveals the best alternatives.

3.1.1.2 Rating and Ranking Methods

The rating and ranking methods provide a direct, but rough, comparison of alternatives. Rating approaches (Carter et al. 1972) typically use a simple + and - scale to indicate the achievement or nonachievement of an objective by a plan. The ratings may then be compared in ordering alternatives. In ranking approaches, alternatives are ordered from best to worst in terms of their achievement of each objective. The objective orderings may then be compared by the decision makers.

3.1.1.3 Matrix and Linear Scoring Methods

Matrix or linear scoring methods usually adopt a model which incorporates both measures of performance (impacts) and public value or preference weightings (see Corps of Engineers, 1972; Crawford et al. 1973, Dee et al. 1972, Leopold et al. 1971). The general form of the model can be written as:

$$\max \sum_{p=1}^{n} W_p B_{ip} \qquad i = 1, 2, \ldots, m$$

where W_p are weights for the p goals with performance B_{ip}, and i is an index on alternatives. The procedure requires prior assessment of weights, and through the multiplicative and additive computations reduces the multiobjective problem to a single valued one. This aggregative procedure does not clarify explicit trade-offs and results in a loss of information.

3.1.1.4 Trade-off Displays and Analysis

This approach aims at organizing quantitative information on the performance effectiveness of alternatives in either graphical form (Bishop 1972) or tabular form (U. S. Water Resources Council 1973, McKee et al. 1978, McKee and Simmons 1978, 1979, McKee 1979, Suhr 1980, McKee et al. 1981) for making comparisons among alternatives. Rather than attempting to explicitly weigh objectives, the decision maker directly examines the trade-offs, usually via paired comparisons, in reaching a preference decision between alternatives. A series of such comparisons yields a preferred solution. The necessity to make many complicated comparisons and choices is an inherent disadvantage of direct trade-offs, but it has the advantage of displaying information on impact trade-offs so that these are accounted for in decisions. Suhr (1980), in his Trade-off Evaluation Procedure, has overcome some of the disadvantages of trade-off displays, and has provided a streamlined process for using trade-off displays.

3.1.1.5 Goals Evaluation Techniques

Goals evaluation techniques are concerned with characterizing and comparing the impacts of alternatives on the achievement of a systematically defined set of goals. Goal evaluation techniques are generally indicator-based, using a broad, hierarchically arranged set of goals as a framework for information display to examine the expected goal achievements design alternatives. The major example of goals evaluation is the Techcom methodology (Peterson et al., 1971, 1974).

3.1.2 Alternative Generating Techniques

This general class of MOP techniques is based on mathematical optimization models. This class has been further subdivided by previous authors (Cohon and Marks 1973, 1975, Bishop et al. 1976a, 1976b) into convenient subclasses, and Cohon and Marks (1973) present an excellent evaluation of several representative multiple objective programming techniques in terms of their computational efficiency, explicitness of trade-offs, and the amount of information produced for decision making. Each of the following subclasses of techniques attempts to identify the noninferior set. However, each employs a different approach.

3.1.2.1 Lexicographic Approaches

Objective ordering or lexicographic techniques (Waltz 1967) require that the objective functions be ordered in a priority sequence. A noninferior point is then generated by sequentially optimizing the objective functions beginning with the highest priority. At each iteration, a constraint is added which restricts the decision variables to the current noninferior set. The process terminates when either all objective functions have been optimized or the noninferior set is restricted to the singleton or null set.

3.1.2.2 Parametric Techniques

Parametric approaches (Geoffrion 1967, Major 1969, Mauglin et al. 1972, Vemuri 1974) write an overall objective function as a weighted sum of the individual objective functions. The weights are usually normalized such that their sum equals one. The noninferior set is then generated by computing the overall optimum for various sets of weights.

3.1.2.3 ε-Constraint Approach

The ε-constraint, or simply constraint, method (Cohon and Marks 1973, Haimes 1975, Miller and Byers 1973) selects one objective function from the rest, and the remaining objective functions are then optimized individually. A final problem is then formulated which utilizes the previously selected objective function and a set of constraints which requires that each of the other objective functions remain within ε of their respective optima.

3.1.2.4 Goal Programming

Goal programming (Charnes and Cooper 1961, Salukvadze 1971, 1974) presents a different approach to the MOP problem. Acceptable levels are established for each of the objective functions and a new optimization problem is composed. The new problem minimizes the deviations of the objective functions from the established acceptable levels. The deviation variables are defined by a set of constraint equations. This set of constraints contains one equation for each of the original objective functions. A variation of the goal programming approach, goal attainment (Gembicki 1973), introduces a weighting function which establishes the relative importance of attaining the acceptable levels for each of the objective functions.

3.1.2.5 Marginal Value Approaches

Another subclass of multiobjective programming techniques attempts to display the marginal trade-off values of the various objectives, that is, given a noninferior point what are the relative values of the next units of each objective. Two representatives of this subclass are the step method (Benayoren et al. 1971) and the surrogate worth trade-off method (Haimes and Hall 1974).

3.1.3 Information Integrating Techniques

Many MOP approaches feature techniques that both organize technical and preference information to systematically identify "better" points on the noninferior surface. This section examines five of the better known of these techniques in some detail.

3.1.3.1 Step Method (STEM)

One of the earliest algorithms reported in the literature which addressed alternative generation and relative value assessment as an integrated package is the STEM algorithm developed by Benayoren et al. (1971). The algorithm incorporates elements of both lexicographic and goal programming techniques in an iterative process requiring the decision maker to trade off absolute quantities of objectives by relaxation of goal attainment levels. The approach can be summarized into the following steps:

1. Determine the single criterion optimum for each objective function and the values of each of the other objective functions of these optimal operating points. This information constitutes what Benayoren et al. (1971) term a pay-off table.

2. Formulate a combined objective function which minimizes the weighted sum of the objectives from their respective single criterion optima. Benayoren et al. (1971) suggest a weighting scheme proportional to the difference between the maximum and minimum entries in the pay-off table. This scheme weights more heavily the objectives which are likely to vary most from their single criterion optimum.

3. Present the combined objective function optima to the decision maker and obtain his assessment of the relative objective achievement. If one or more of the objectives is determined to be unsatisfactory, the decision maker must specify at least one objective which can be decreased (relaxed). The combined objective function is then modified by assigning weights of zero to the relaxed objectives. The feasible region in decision space is modified by constraining all objectives to be better than the previous levels of attainment reduced by the relaxation amount where appropriate. This step is repeated until the decision maker is satisfied with the current attainment set.

The convergence of the algorithm can be argued from a heuristic point of view to be in less than one iteration for each objective. This follows from the logical inconsistency involved on the decision maker's part in including an iteration which relaxes an objective which he wants improved. Benayoren et al. (1971) have also developed a means for aiding the decision maker in selecting the objectives to be relaxed. By solving a second optimization problem, estimates are generated for the variation in one objective induced by relaxation of another objective.

3.1.3.2 Sequential Multiobjective Problem Solving

A second early algorithm appearing in the literature was developed by Monarchi et al. (1973). The algorithm, sequential multiobjective problem solving (SEMOPS), is a relatively pure application of goal programming embedded in an interactive algorithm. The decision maker begins by assigning attainment constraints to each objective. These constraints can be described by equalities, half infinite intervals, or compact intervals. The next task required of the decision maker is to partition the set of objectives into two classes, termed goals and aspirations. The distinction between these classes is the rigidity of the attainment level. Goals have rigid attainment levels associated with them and aspirations allow more deviation from the _a priori_ levels assigned by the decision maker. Utilizing the information extracted from the decision maker, a single criterion optimization problem is formulated which minimizes the sum or product of a set of penalty functions reflecting deviations from the specified attainment levels. Based upon the results obtained from the optimization problem, the decision maker is given the opportunity to change attainment levels and/or move objectives between the goal and aspiration sets. The optimization problem is then reformulated and resolved. The process continues until the decision maker is satisfied with the results of the optimization problem. The algorithm can be stated in three steps:

1. Interact with the decision maker to obtain attainment level and classification information on the objectives.

2. Formulate and solve a single criterion optimization problem based upon penalties for deviation of objectives from specified attainment levels.

3. Report results of the optimization problem solution to the decision maker. If he is satisfied, stop; otherwise, return to step one.

3.1.3.3 The Surrogate Worth Trade-off Method

Another approach which integrates the alternative generation and value tradeoff aspects of multiple objective decision making is the surrogate worth trade-off method, proposed by Haimes and Hall (1974), Haimes et al. (1975), and others. This approach uses the utility concepts discussed in Chapter 2 as a rational decision model. Consequently, the tangency property between the noninferior surface and the decision maker's indifference curves is exploited to identify the best compromise solution.

The tangent plane of the indifference curves, as a function of the various objective attainment levels, is identified by direct interaction with the decision maker. The noninferior set tangent is also determined as a function of the objective attainment levels. This is done by utilizing some of the duality relationships between the Kuhn-Tucker multipliers (dual variables) and the objective constraint set inherent in the ε- constraint alternative generation methodology. The tangent plane parameters can then be computed from the dual variables. The algorithm can be described by the following sequence of steps:

1. Determine the single-criterion optimum for each objective (F_i).

2. Identify a set of noninferior alternatives and their respective dual variables (shadow prices) by utilizing the ε-constraint method, as described earlier; each objective must be used as the objective function for several noninferior alternatives; compute the trade-off functions for each alternative (tangent plane parameter).

3. Determine the functional relationship between the objective attainment levels (F_i - ε_i) and the noninferior surface tangent plane parameters; regression analysis is suggested.

4. Determine the decision maker's indifference curve tangent by asking him to rate changes in the objective attainment levels between noninferior alternatives on an arbitrary numerical preference scale.

5. Identify the decision maker's indifference curve tangent plane parameters functional dependence upon the objective attainment levels; again regression is suggested.

6. Compute a candidate best compromised solution (the point at which the two sets of tangent parameters differ at most by a constant) using the functional relationships developed in steps 3 and 5. In terms of the objective attainment levels, compute the noninferior surface tangent plane parameters by solving an ε-constraint multiobjective problem using the candidate best solution objective attainment levels.

7. Verify that the decision maker is indifferent to the marginal (small perturbation) changes in objective attainments; if so, stop; if not, repeat steps 2 through 7 using noninferior alternatives closer to the current candidate in the best compromise solution.

3.1.3.4 Objective Space Gradient Approach

Dyer (1973), Dyer and Saron (1977), Geoffrion (1970) and Geoffrion et al. (1972) have proposed what is generally known as the "Geoffrion, Dyer, and Feinberg" approach. The basis of this approach is a gradient search in the objective space seeking the optimum of the utility function. Since the mathematical form of the utility function is unknown, the decision maker is asked to provide the required utility gradient information directly. This is in the form of trade-off ratios among the objectives which, after a few normalization operations, can be related to the utility function gradient by application of the chain rule of differentiation.

The search direction is then determined by optimizing the utility gradient in decision space. Several alternative operating points are then generated along the ray in decision space defined by the current point and the optimum gradient. The decision maker is then asked to choose the "best" alternative. The decision maker provides the utility trade-off ratios at the new point, thus beginning the next iteration. The process terminates when the decision maker is satisfied with the current point.

3.1.3.5 Trade-off Cutting Plane Algorithm

One of the most recent integrated algorithms has been developed at Purdue by Musselman and Talavage (1979). Their approach is unique and possesses convergence properties which are unobtainable by the other algorithms described in the literature. The idea was spawned by a desire to reduce the amount of information required from the decision maker in applying the objective space gradient algorithm. The concept was to eliminate the step size problem and replace it with a technique which does not require as much decision maker interaction. The methodology which the algorithm incorporated accomplished the objective but changed the entire character of the approach. The trade-off cutting plane algorithm generates a sequence of nested sets in the objective space rather than a sequence of search directions. The result of this change is that unlike any of the other algorithms, convergence can be proven.

The methodology is based upon a numerical procedure for locating the center of a compact convex set developed by Huard (1967, 1968). The procedure is to reduce the feasible region in objective space by forming a cutting plane utilizing information about objective function trade-offs at a particular operating point. The cutting plane is then transformed into decision space. The center of the set formed by the intersection of the original constraint set in decision space and the trade-off cutting plane transformed to the decision space is then taken as the next operating point and the process is repeated.

The most important properties which Musselman and Talavage were able to prove are: 1) convergence, 2) the best compromise solution lies in the intersection of the nested sets, and 3) extension to discrete problems. From a theoretical standpoint, these three characteristics make this the most important algorithm thus far proposed for solution of multiobjective problems.

3.1.4 Summary of MOP Techniques

In concluding the literature review, a few observations about characteristics of the existing algorithms are appropriate.

These observations also serve to motivate and introduce the algorithm developed in this research. The comments here are directed toward the integrated algorithms since the nonintegrated techniques are taken to be building blocks from which complete solution strategies can be built.

The first of these observations is that of the five algorithms discussed, only one, the surrogate worth method, actually insures that the selected best compromise solution is in fact noninferior. The SEMOP algorithm ignores noninferiority of points completely and the other three rely heavily on the decision maker to recognize a noninferior solution when presented with one.

The second characteristic is that each algorithm requires the decision maker to deal with the objectives individually either by setting attainment levels or relaxation levels in absolute terms or by providing marginal value trade-off ratios between parts of objectives. These very detailed sets of numbers are difficult and cumbersome for the decision maker to provide and inconsistencies in this information can adversely affect algorithm performance.

The last observation is that only one of the five algorithms, the trade-off cutting plane, actually generates a convergent sequence of trial best compromise solutions. The others rely upon the decision maker stopping the process at an appropriate time. Two of these algorithms, SEMOP and objective space gradient, do not provide a basis of comparison for attainable operating points, since they only solve single criterion problems.

The algorithm developed in this research addresses these three problems by: 1) identifying the noninferior set a priori and insuring that the algorithm solution is in the noninferior surface; 2) interacting with the decision maker by having him identify a preferred alternative from a group of alternatives without having to provide any further details, especially with regard to slope; and 3) generating a sequence of nested sets similar to that generated by the trade-off cutting plane algorithm.

3.2 A CRITIQUE OF MOP APPROACHES

As reported by Bishop et al. (1976a, 1976b), the multiple objective approaches described above are efforts to provide a rational model for water resources planning decisions. Working on the technical side of Figures 2.1 and 2.2, the planning team employs, in so far as possible, data and analytical tools in assessing the physical aspects of plans to define the production possibilities frontier. While the engineer-planner is generally committed to a rational model, much of what actually happens in practice is based on art and experience and limited by resources and time. Thus, the planning team does not exhaustively search for all alternatives in the noninferior set, but rather generates a number of discrete plans based on both analysis and judgment with no a priori guarantee of noninferiority.

In the larger context of interfacing with public interests and decision makers, the planning activities of Figure 2.3 generate the social indifference functions of Figure 2.1. In this sense, the planning process is a normative and behavioral model for resource value allocations effectuated through the political decision structure and social change. The lead planner and public decision makers, through bargaining mechanisms, eliminate or reformulate alternatives in the noninferior set in accordance with preference values, to arrive at a solution which has the necessary coalition of support to achieve implementation.

The application of multiobjective methods in the planning process, then, may appropriately serve either or both of two functions: 1) as a rational decision making model in developing a set of noninferior alternative plans, and 2) as a behavioral model to facilitate decision making in arriving at a preferred alternative. With this in mind, the final section of this chapter overviews the major classes of multiple objective techniques in relation to the rational and behavioral aspects of the planning process, the degree to which these techniques fulfill the requirements for MOP techniques proposed in the previous chapter, and the implications for structuring the planning process.

3.2.1 Technical Planning Content and MOP Methods

The attributes of the major classes of multiple objectives in relation to the technical content of the planning process is summarized in Table 3.1. Methods I-IV involve procedures for contrasting the impacts (benefits and costs) of alternatives once they have been formulated. However, procedures I, II, and III aggregate information, tend to obscure real trade-offs, and can lead to faulty decision making. Because of their simplicity and low-level data requirements, when used with caution they may be useful early in the planning process to eliminate alternatives that are obviously dominated. By contrast, the procedures under Method IV explicitly delineate trade-offs and therefore highlight, rather than obscure, the basis of decisions. They do not, however, ensure the generation of noninferior alternatives. Multiple objective programming (V) and goals evaluation (VI) methods offer a strong overall organizing concept for the process. The goals evaluation approaches, however, also tend to obscure trade-offs in the extensive indexing of information that is used. Overall, the multiple objective programming approaches offer the best basis for the detailed and comprehensive analysis needed to generate the noninferior alternatives and describe their trade-offs.

Table 3.1. Attributes of multiobjective methods relative to planning process technical content.

Method (1)	Problem Description: Identifies Decision Variables in Relation to Objectives (2)	Resource Capability: Defines Feasible Decisions in Relation to Resource Limits (3)	Alternative Plans: Generates the Complete[a] Set of Noninferior Alternatives (4)	Performance Effectiveness: Describes Trade-offs Explicitly (5)	Evaluation and Selection: Communicates Information in a Form that Facilitates Compromise (6)
I. Visual Techniques	Implicit	Yes	No	No	Yes
II. Rating and Ranking	Implicit	No	No	Yes - Qualitative	Yes
III. Matrix and Linear Scoring	Explicit	No	No	No - Aggregates	No
IV. Impact Trade-off Displays	Explicit	Yes	No	Yes - Quantitative	Yes
V. Multi-objective Programming					
A. Objective Ordering	Explicit	Yes	No[c]	No[b]	No-Insufficient
B. Parametric	Explicit	Yes	Yes	Yes - Quantitative	No-Abstract
C. Constraint	Explicit	Yes	Yes	Yes - Quantitative	No-Abstract
D. Goal Programming	Explicit	Yes	No[c]	No	No-Insufficient
E. Marginal Value Trade-offs	Explicit	Yes	Yes	Yes - Quantitative	Yes
VI. Goal Evaluation - Techcom	Explicit	No	No	No	No

[a]Generates the noninferior set of all weighting functions of interest.

[b]Could be formulated in such a way to produce trade-off information.

[c]Uses only one rank ordering of objectives.

3.2.2 Social Value Content and Multiple Objective Methods

For the behavioral aspects of the planning process, the characterization in Table 3.2 gives an indication of the extent to which the multiple objective methods incorporate social values content into the planning process. With the early thrust of the planning activities directed toward developing alternatives, method VI which has a systematically defined goal structure can be particularly useful. If the planner adopts inappropriate sets of objectives, the alternative plans will likewise be inappropriate. Formulating appropriate alternatives can be further guided, as in V and VI, by social and policy constraints, and the ranges of weightings of objectives which imply acceptable alternative futures.

When the process emphasis shifts to evaluation of alternatives, methods that provide opportunity for publics to express preferences for trade-offs and bargain to reach a compromise solution are needed. It is in this multiple decision maker aspect of multiple objective problems that present methods are particularly lacking.

3.3 SUMMARY

The overall objective of the planning process is to arrive at a preferred plan subject to constraints on data, staff, time and budget availability. To meet this objective requires the efficient production and integration of both the technical and value content of the planning process. Evolving multiple objective methods offer the planner a number of new options for analysis evaluation and decision making.

While it is difficult to make definitive statements that apply without exception to all techniques within a class of methods, Tables 3.1 and 3.2 at least provide a general indication of attributes that are of concern in employing appropriate multiple objective methods.

Table 3.2. Attributes of multiobjective methods relative to planning process value content.

Method (1)	Goals and Objectives: Provides a Framework for Articulation of Objectives (2)	Standards and Constraints: Defines Feasible Decisions in Terms of Policy and Social Constraints (3)	Alternative Futures: Uses Preferences for Objectives to Define a Set of Socially Desired Alternatives (4)	Trade-off Preferences: Provides a Mechanism for Publics to Express Preferences for Trade-offs Between Alternatives (5)	Evaluation and Selection: Facilitates Decision-makers Interaction and Bargaining in Converging to "Best Compromise" (6)
I. Visual Techniques	Ad hoc	Yes	Yes - *a priori*	Yes - indirectly	Yes
II. Rating and Ranking	Ad hoc	No	No	No	No
III. Matrix and Linear Scoring	Ad hoc	No	No	No	No
IV. Trade-off Displays	Ad hoc[a]	Yes	No	Yes - directly	Yes
V. Multi-objective Programming					
A. Objective Ordering	Systematic	Yes	Yes - *a priori*	No	No[c]
B. Parametric	Ad hoc	Yes	No	No[b]	No[c]
C. Constraint	Ad hoc	Yes	No	No[b]	No[c]
D. Goal Programming	Systematic	Yes	Yes - *a priori*	No	No[c]
E. Marginal Value Trade-offs	Ad hoc	Yes	No	Yes - directly	Yes-Iterative
VI. Goal Evaluation - Techcom	Systematic	Yes	Yes - *a priori*	Yes - directly	No

[a]Water Resources Council P & S does systematically enumerate goals.

[b]Could through extensions in the analysis.

[c]Could be implemented so as to accommodate group interactions.

CHAPTER 4.0

A NEW MOP TECHNIQUE

4.1 DESCRIPTION OF THE METHODOLOGY

In designing a multiple objective planning technique for this study, attention was paid to both the theoretical concerns of Section 3.1.3.5 and the practical consideration and limitations of multiple objective planning discussed in Chapter 2 and sections 3.2.1 and 3.2.2. The basic mathematical idea of the algorithm which is described in this section, called the "Vector Optimization Decision Convergence Algorithm" (VODCA), is to generate a sequence of nested sets which all contain the best compromise solution. This is done in a manner which ensures consideration of all noninferior alternatives and which obtains preference information from the decision maker (DM) in a way he finds comfortable.

Figure 4.1 illustrates the basic geometry of the VODCA algorithm for a well-conditioned, two-dimensional multiple objective problem. In the figure, the nested sets are the regions between the noninferior surface and the utility function contours. The constraint planes are constructed so that they include (pass through) the intersection of the noninferior surface and the utility contour which maximizes utility over the previous constraint plane. Thus, each successive utility contour removes some of the feasible region in objective space from further consideration.

Two separate pieces of information are required from the DM at each iteration. First, he must identify the best alternative on the constraint plane from among the

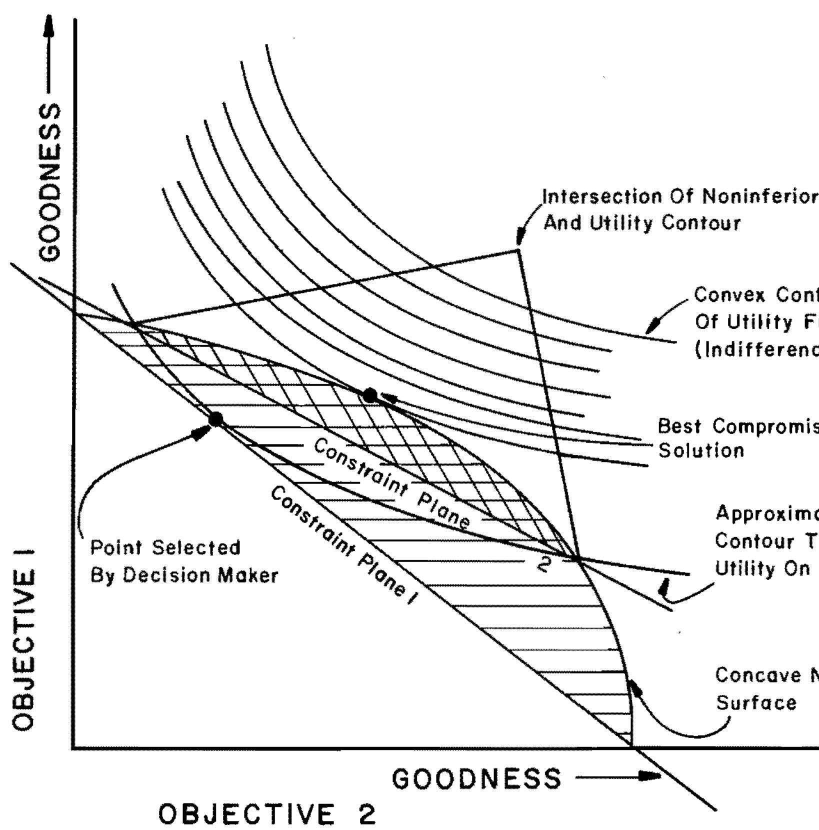


Figure 4.1. A well-conditioned multiple objective problem.

feasible alternatives. Second, information regarding the local shape of the utility contours must be provided. Both pieces of information are gleaned from the DM through interaction with the VODCA computer algorithm. The steps in this interaction are described in Section 4.1.2.3.

The VODCA algorithm can be summarized in the following steps:

1. Identify the noninferior surface and feasible region in objective space.

2. Construct an approximation of the utility function based upon information obtained from the DM.

3. Use the utility function approximation to eliminate a portion of the feasible region.

4. If convergence is obtained, stop; otherwise, go to step 2.

The general organization of the algorithm is presented in the next few pages, followed by a detailed description of each procedure, and finally followed by the theoretical aspects of the approach.

4.1.1 General Algorithm Organization

Figure 4.2 represents the sequence of procedural steps required to implement the general concept presented in Figure 4.1. The process begins by constructing a functional representation of the noninferior surface. The first two procedures in the flow diagram accomplish this task. This also ensures consideration of all noninferior alternatives. The third procedure is a one-time preparation for the first DM interaction, the explanation of which will be given in the next section. The interaction with the DM is the beginning of the iterative process which will yield the best compromise solution. This step is comprised of the DM evaluating a selection of alternatives. The alternatives which will be presented will all lie on the current constraint plane and the evaluation is done on the basis of an arbitrary relative scale. By combining the information provided by the DM from several constraint planes, sufficient information is obtained to approximate the utility function. Thus, by repetition of the same DM interaction process, both pieces of information required from the DM are obtained.

The check on consistency shown in Figure 4.2 as the next process is included for two purposes. First, if there are inconsistencies in the information the DM provides, it will bring to the attention of the DM that the most recent selection of a preferred alternative from a constraint plane is radically different from the alternative anticipated by extrapolation of the previous selections the DM has made. Secondly, this step indicates when the best compromise

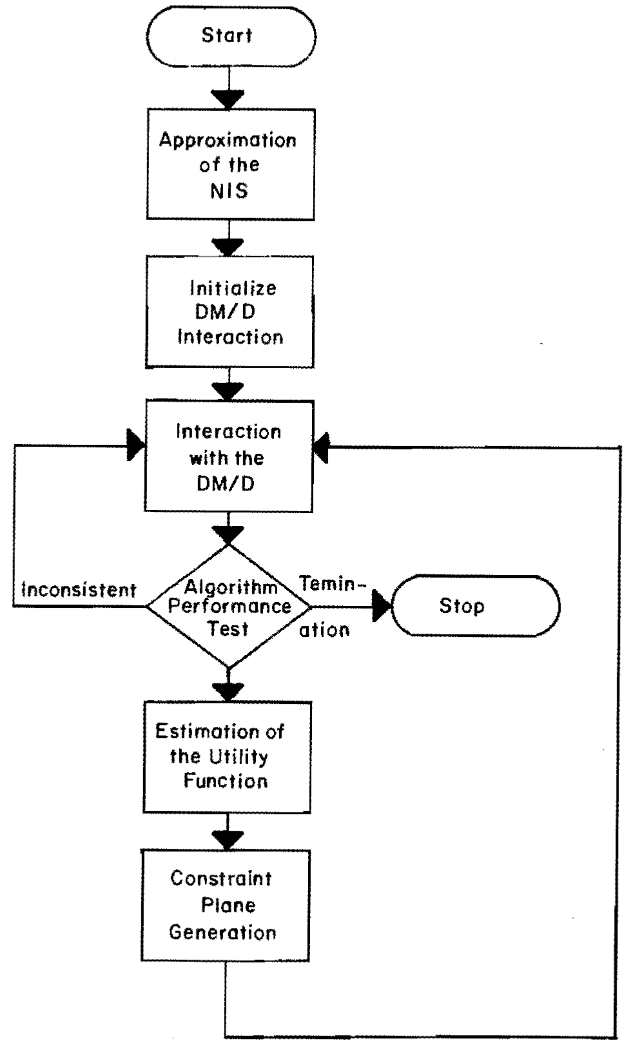


Figure 4.2. VODCA procedures.

solution has been excluded from the remaining alternatives under consideration.

The convergence tests which follow the consistency tests include the normal mathematical definitions of convergence, such as the remaining alternatives (g's) are within a prespecified stopping distance of one another. However, these tests also include the DM terminating the process by indicating an inability to distinguish preferences among the alternatives presented during the interaction process.

The approximation of the utility function, along with the functional representation of the noninferior surface, forms the core of the VODCA algorithm. The approach is to select from a prespecified family of functions (quadratic, cubic, translog, Stone-Geary, etc.) the member which solves the simultaneous equations which result from imposing the necessary conditions to several constrained optimization problems, in the sense of minimum squared error. The DM has provided the solution to the constrained problems during the interaction process. The equations which are necessary conditions for a local optimum must then hold at each of the alternatives (points in objective space) selected by the DM interaction. Thus the optimal parameters can be computed for the approximating function.

The final two procedures in the iterative loop are preparation for the next DM interaction. The next constraint plane from which points are to be selected must pass through the intersection of the utility function contour tangent to the previous constraint plane and the noninferior surface. To compute the coefficients for the constraint plane, n points must be identified in the intersection of the noninferior surface and the tangent utility function contour, where n is the number of dimensions in objective space. The last two processes find the required points and compute the coefficients, respectively.

Since convergence of the algorithm depends upon information obtained from the DM and is thus subject to inconsistencies and errors, a final test is included prior to termination to verify that the identified best compromise solution actually reflects the DM's preferences. The verification is composed of a final DM interaction, with the points presented for evaluation being chosen from the noninferior surface in the neighborhood of the estimated best compromise solution. The estimated best compromise solution is also among the alternatives. Verification is accomplished by the DM choosing the estimated best compromise solution as the preferred solution.

4.1.2 Principal Components of the Algorithm

The VODCA algorithm follows three steps in solving the multiple objective problem. Initially, the algorithm requires an analytical expression of the noninferior surface. Second, VODCA uses the Trade-off Evaluation Procedure (TEP) (Suhr 1980) for obtaining useful preference information from the decision maker. Finally, the algorithm utilizes this preference information to estimate the parameters of a utility function. The mechanisms followed in these three steps are discussed in the following sections.

4.1.2.1 Estimating the Noninferior Surface

The VODCA algorithm requires an analytical expression from which points that lie on the noninferior surface can be readily identified. To ascertain the required expression a specific functional form was used to approximate the noninferior surface. In any functional approximation procedure, the essential ingredient is information about the function to be approximated. The more information available about the function, the better the approximation will be (assuming all the information is of the same quality). The information usually available for obtaining functional approximations is a set of coordinates of points which lie on the graph of the function to be approximated. Occasionally, derivative information is also available about the function at the graph points. (The case where only derivative information is available falls in the purview of differential equations and is excluded from this discussion.)

Chapter 3 presented several methodologies for generating information concerning the noninferior surface. These approaches are well documented in the literature. Within this large selection of approaches are two that are particularly well suited for the purpose of functionally approximating the noninferior surface. These are the parametric approach and the ε-constraint approach. Their suitability for generating information required to approximate the noninferior surface is based upon the generation of tangent plane information as well as coordinate information at noninferior points.

The functional approximation to the noninferior surface can be obtained by either the traditional regression using only coordinate information or by using a modified regression incorporating the derivative information. Since many problems of practical significance involve considerable expense for each solution of the parametric or ε-constraint problem, there is an economic incentive for reducing the number of noninferior points which must be generated. Table 4.1 demonstrates the dramatic economics which can be achieved by utilizing derivative information. The table entries are the minimum number of noninferior points required to determine the parameters of a quadratic approximating function for various objective space dimensions.

Use of the derivative information in determining the minimum squared error parameters for the functional approximation is made by solving the optimization problem:

$$\min_{p} \sum_{j=1}^{N} \sum_{i=0}^{\ell-1} (f_i(g^j,p) - D_i^j)^2$$

where

- N is the number of noninferior points
- ℓ is the dimension of the objective space
- p is the parameter vector for the approximating function f
- f_i is f for i = 0 and $\partial f/\partial g_i$ for i = 1, 2, ... ℓ-1
- D_i^j is the noninferior surface information at the j^{th} noninferior point

$$D_0 = g_{\ell p}\,(g^j)\,D_i^j = \lambda_i\,(g^j) \quad i = 1, 2, \ldots, \ell\text{-}1$$

and we assume an approximation of the form $g_\ell = f(g_1, g_2, g_3, \ldots g_{\ell-1})$

Any optimization technique which will solve this problem can be used to obtain the parameter vector. However, since most approximating functions will be linear in the parameters it would be desirable to be able to use a standard linear regression technique to obtain the results. As will be demonstrated in the example, this is easily accomplished by proper construction of the data set for a regression package.

4.1.2.2 Estimation of the Utility Function

One of the major purposes of this research has been to develop a technique for obtaining the required relative value information from the DM in a manner a nontechnical person would find comfortable. The information necessary to identify the best compromise solution is indifference curve tangent information. The approach is to ask the DM to solve a constrained optimization problem by simply evaluating on an arbitrary scale a group of alternatives presented to him. The alternatives are selected from a constraint plane passing through the feasible region in objective space. Using an interpolation scheme described in the DM interaction discussion, a best alternative on the constraint plane is found. Applying the Kuhn-Tucker conditions to one or more of the constrained optimization problems with known solutions allows estimation of the parameters of a utility approximation function. The mathematics of the approach can be stated as:

$$\max_{g} \quad UF(g,p)$$
$$\text{STC} \quad c^k g = c^k{}_{\ell+1}$$

where UF is a known functional form

p is a parameter vector for UF

g is a point in objective space

c^k is the constraint plane parameter vector for the k^{th} constraint plane

Writing the Kuhn-Tucker conditions yields:

$$\nabla_g\, UF\,(g,p) - \lambda^k\,\{(c^k\}^T = 0$$

$$c^k \cdot g = c^k_{\ell+1}$$

Since the optimal g, g^*, is provided by the DM, we have

$$\nabla_g\, UF\,((g^k)^*,p) - \lambda^k\,\{c^k\}^T = 0$$

$$c^k \cdot (g^k)^* = c^k_{\ell+1}$$

Several observations can be made regarding these sets of equations:

1. For each constrained problem (indicated by k), g^* and C are known and p and λ are unknown.

2. The constraint equations contain only known information and are consequently not useful in determining p.

3. For each constrained problem, at most ℓ-1 parameters can be determined from the equations.

4. The set of useful equations is homogeneous.

5. The minimum number of DM interactions is a function of both the objective space dimension and the number of parameters in the approximating family.

There are several major considerations in obtaining solutions to the set of estimating equations. The first consideration is the order of the sets of equations. The proper order to obtain a unique solution occurs only when:

$P = m(\ell-1) - 1$

ℓ = objective space dimension

m = number of constrained problems

P = number of parameters

Table 4.1 illustrates this point for the family of quadratic approximating functions, assuming one unknown is arbitrarily chosen because of the homogeneity. Entries corresponding to $\ell = 2$ and $\ell = 5$ reflect uniquely determined sets of equations. It should be noted that the case of an underdetermined set of equations will never arise since the addition of more constrained optima (DM interactions) to the equation set converts it to a uniquely determined or overdetermined set.

There are two possible resolutions to the problem of estimating from an overdetermined set of equations. The first and simplest is to delete the excess equations.

Table 4.1. Minimum number of noninferior points required to determine quadratic approximation of the noninferior surface: $g_k = f(g_1, \ldots g_{k-1}, g_{k+1}, \ldots g_\ell)$.

Objective Space Dimension	Number of Points Without Derivative Information	Number of Points With Derivative Information
2	3	2
3	6	2
4	10	3
5	15	3

This approach has major disadvantages in that it requires DM interactions to yield highly consistent results since the estimating function must be exactly tangent to the plane at the specified points, and it discards information which is available with no additional effort. The second and preferred resolution is to solve the complete set of equations in a minimum error sense. The traditional least squared error criterion has a great deal of appeal since it yields linear estimation equations if the functional family is linear in the parameters.

A second consideration in estimating the utility function is that the estimates must yield contours which satisfy a convexity or concavity property depending upon whether the objectives are being maximized or minimized. If these properties are not satisfied the basic premise of the multiple objective problem is violated, that is the problem has been improperly formulated (Baumol 1977).

A general functional form that satisfies both of these considerations is the Stone-Geary, also known as the Klein-Rubin utility function. Using a Stone-Geary formulation of the utility function of the type

$$UF = \prod_{i=1}^{n} (x_i - \gamma_i)^{\alpha_i}$$

where

n = dimension of the objective space

x_i = level of the ith objective

γ_i = a preselected arbitrary constant

α_i = an exponent selected such that

$$0 \leq \alpha_i \leq 1 \text{ and } \sum_{i+1}^{n} \alpha_i = 1$$

The problem of estimating the parameters of the utility function becomes one of estimating the α's. For the Stone-Geary function, the α's can be computed as:

(1) Maximize UF subject to a linear constraint $Px = I$ where P is an n-component row vector and I is a constant

(2) The optimum value of x_i is

$$x_i = \gamma_i + \frac{\alpha_i}{p_i} \left(I - \sum_{j=1}^{n} p_j \gamma_j\right) \quad i = 1, 2, \ldots, n$$

(3) The least square estimator of α_i is therefore

$$\alpha_i = \frac{\sum_k \left[(x_{ik} - \gamma_i)(I_k - \sum_{j=1}^{n} p_{jk}\gamma_j)/p_{ik}\right]}{\sum_k \left[(I_k - \sum_{j=1}^{n} p_{jk}\gamma_j)/p_{ik}\right]^2}, \quad i = 1,2,\ldots,n$$

4.1.2.3 Interaction with the DM and Estimation of the Constrained Optima

The selection of a best compromise solution to a multiple objective decision problem requires knowledge of some information about the DM's preferences among objectives relative to one another. Although preference information is required to solve the problem, the formulation of the problem as multiple objective presumes that a clear mathematical statement of preference among alternatives is not possible. If such a mathematical formulation were possible, the problem would condense into a classical single objective problem.

The essential point of a multiple objective decision situation is that the relative value of the objectives is a strong function of the position of the alternative point the DM is asked to consider. That is, if a DM is asked to provide the relative value of objectives 1 and 2 at point g^1 (for example, 2 units of objective 1 are equal to 1 unit of objective 2), the same question might elicit a vastly different response at point g^2. For this reason, many theorists in the MOP field believe that techniques which make use of _a prior_ weighting schemes should not be used. The DM interaction incorporated in the VODCA algorithm obtains the preference information implicitly through a series of evaluations of selected alternatives. The evaluations are accomplished through a set of interactions designed to aid the DM organize his decision making process and simultaneously document the basis for his conclusions. The basis for this process is Suhr's TEP methodology (Suhr 1980). The alternatives which are used in the evaluation process are chosen from a fairly restrictive region in objective space and the process is used repeatedly as the algorithm converges. Thus, the VODCA algorithm is always using preference information applicable to the region in objective space where the utility function estimate will be used.

The interaction with the DM uses one form of the Trade-off Evaluation Procedure recommended by Suhr (1980). Other variations on the procedure are considered superior (McKee et al. 1981), but would be unwieldy for application in VODCA. TEP is used by VODCA to evaluate the alternatives from a given tangent plane in order to provide a numerical score for each alternative; the scores are then used to estimate the location in the plane of the constrained optimum. TEP obtains these numerical scores, which are intended to represent the relative desirability of one alternative versus another, without using _a prior_ weighting approaches. It should be stressed that the portion of TEP used in VODCA pertains only to the evaluation phase of the planning process and not to the whole process, as TEP does. The TEP mechanisms used in VODCA, however, do provide a means for documenting the DM's viewpoints regarding the trade-offs examined in the process of arriving at a preferred alternative.

The interaction with the DM begins with the algorithm displaying a blank "personal value graph" (Figure 4.3a) for each objective. Note in Figure 4.3 that the algorithm uses the term "factor" for "objective." This is consistent with terminology used by Suhr (1980) and McKee et al. (1981). This value graph consists of a blank graph, the abscissa of which measures the values of a given objective for the alternatives, and the ordinate of which represents a "personal value scale," which ranges from 0 to 100. The DM is to draw his value graph in the space provided indicating his preference for the various values of the objective, assuming the values of other objectives do not deviate outside a small neighborhood around the "local" value (Figure 4.3a). Zero on the value scale represents the DM's least-preferred level of the objective (within the range of objective values specified), and 100 represents the most-preferred level. When properly filled in (for example, Figure 4.3b), each value graph will have at least one point with a "personal value" of zero, and at least one other point with a value of 100. Ordinates corresponding to the abscissas of alternatives are then scaled off of the value graph and entered into the computer. This is done for each objective.

Next, the algorithm displays a table (Figure 4.4) of most- and least-preferred values for each objective and the difference between these. The DM must then do two things. First, he must decide which difference (not which objective) is most important to him. This one is assigned a weight of 100, and the reasons for selecting this difference as being most important are specified by the DM and recorded. The second thing the DM must do is assign relative weights to the other differences. This is done for each difference according to how important the DM thinks the difference is relative to the most important differences identified above. The DM's reasons for these assignments should also be given and recorded. This process of assigning weights to differences is called "indifference scaling" by Suhr (1980). It is used in TEP to provide a numerical indication of how the DM views the range of trade-offs among the alternatives.

After the "indifference scaling" is completed by the DM, the weights thus identified are entered into the computer. The algorithm then computes a composite score, A_i, for each alternative according to the formula

$$A_i = \sum_j W_j V_{ij}$$

where

A_i is the composite score for the i^{th} alternative

W_j is the weight supplied by the DM for the j^{th} factor/objective difference in the indifference scaling procedure

V_{ij} is the score for the j^{th} objective of the i^{th} alternative obtained from the value graph procedures

These composite scores are used by VODCA in a multiple regression to compute the coefficients of a quadratic function relating the A_i's to objective values. The planar constrained optimum is then found by maximizing this quadratic function subject to one linear constraint, that being the plane itself. If the resulting point passes a consistency test (discussed in the following section), it is used as the constrained optimum for the next iteration of calculations.

As previously discussed, the VODCA algorithm proceeds by successively eliminating a portion of the feasible region in objective space through generation of a sequence of planes. These planes separate the noninferior set into two subsets, one of which contains better feasible alternatives and the other contains worse feasible alternatives. The algorithm eliminates from further consideration alternatives in the latter of these two sets. The bases for constructing this cutting plane are the two properties of utility function contours (indifference curves): 1) they never cross, and 2) the contours represent monotone increasing utility levels (Baumol 1977).

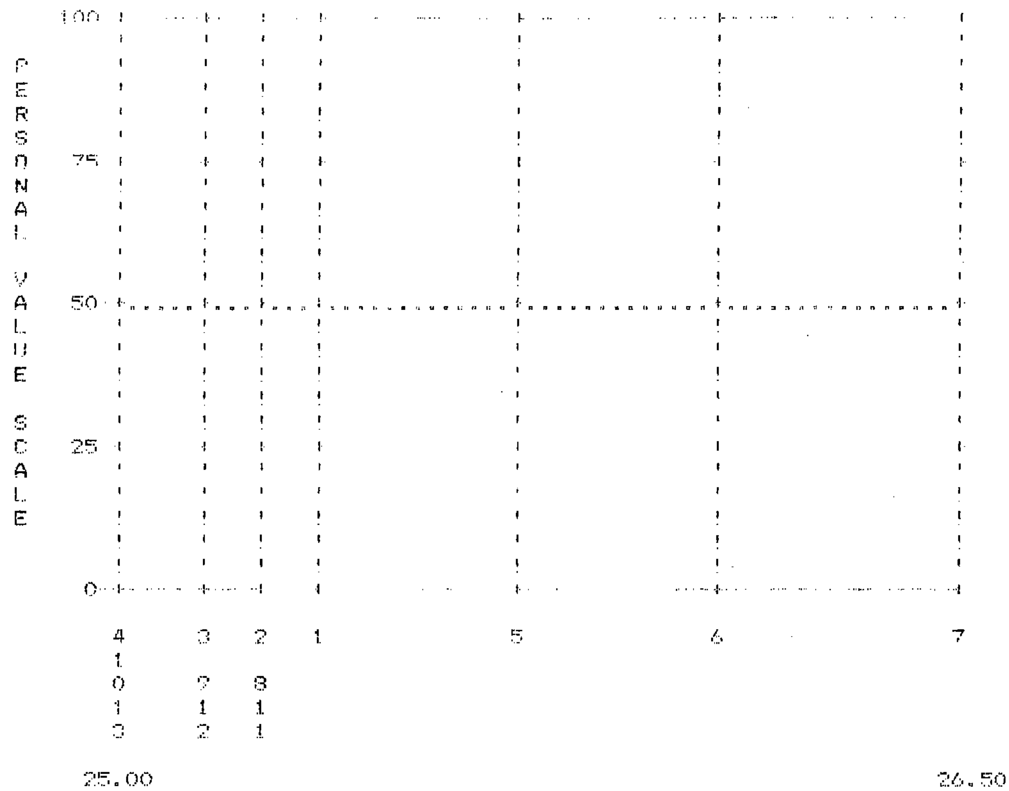
The particular plane that achieves the desired separation of the feasible region is the one which contains the intersection of the current utility contour under consideration and the noninferior set. Figure 4.5 depicts these concepts graphically. Generation of the desired plane then requires two relatively simple steps: 1) generate points which lie in the intersection of the noninferior and utility contours sets, and 2) determine the parameters of the plane passing through the points generated in step one.

4.1.2.4 Convergence, Consistency, and Verification Tests

All numerical algorithms which employ an iterative process intended to converge to some type of prespecified end point (such as a functional optimum or value of an integral) incorporate tests on algorithm performance. Multiple objective optimization algorithms are not exceptions. In fact, because interaction with DM's is required to achieve convergence, a greater variety of algorithm performance testing is required. The tests contained in the VODCA algorithm are divided into three categories as follows:

1. Convergence test: These tests are intended to identify conditions for termination of the algorithm. They are performed at each iteration and include abortive conditions.

2. Consistency test: Consistency tests are designed to indicate conditions which require corrective action. The corrective action to be taken is a reestimation of the



VAL.ADDED AG. (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	25.38
2	25.26
3	25.15
4	25.00
5	25.71
6	26.05
7	26.50
8	25.26
9	25.15
10	25.00
11	25.26
12	25.15
13	25.00

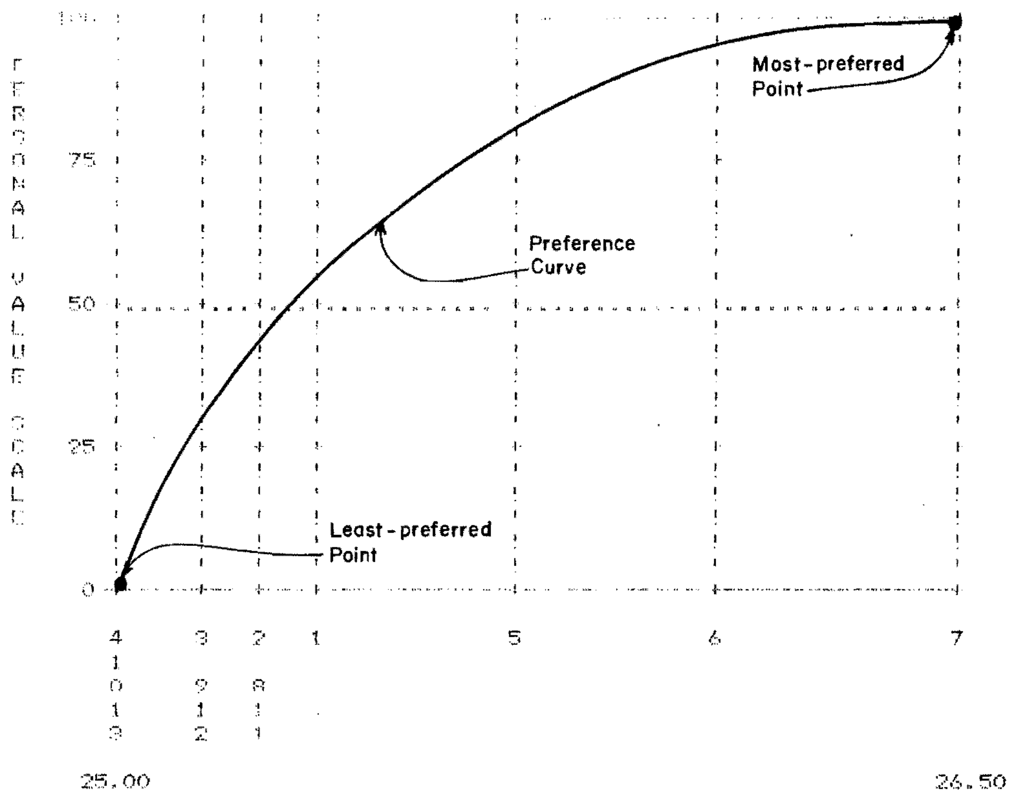
			RANGES ON FACTORS				FOCUS
1	VAL.ADDED AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.[illegible]

Figure 4.3a. Display used in eliciting the intraobjective scale factors.

utility function based upon a revision in DM provided information. A test incorporated in the VODCA algorithm also identifies possible exclusions of the best compromise solution from the set of remaining alternatives. This test is performed every iteration.

3. Verification test: The intent of the verification test is to provide a final check on algorithm performance and DM preference consistency. The test is performed post convergence and the results simply reported to the DM.

Convergence Test: The types of conditions indicating that a multiple objective algorithm should be terminated are similar to those occurring in classical optimization.



VAL.ADDED-AG. (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	25.38
2	25.26
3	25.15
4	25.00
5	25.71
6	26.05
7	26.50
8	25.26
9	25.15
10	25.00
11	25.26
12	25.15
13	25.00

			RANGES ON FACTORS				FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED-ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.39

Figure 4.3b. Display filled in.

Basically, the numerical test should reflect the condition that significant progress toward convergence is no longer being made. This condition can result from the fact that convergence has already taken place, or that the algorithm has somehow failed, or that the problem is ill-conditioned. While classical numerical tests based upon objective function information cannot be used in the multiple objective case, those classical tests based upon operating point information along with absolute limits on procedures are applicable:

1. The maximum number of iterations is exceeded (abortive).

2. The DM is unable to provide the required information (conveyed or abortive).

3. The changes in the constrained optima are too small.

TABLE OF CRITICAL DIFFERENCES:

FACTORS	UNITS	MOST PREFERRED	LEAST PREFERRED	DIFFERENCE	WEIGHT
1 VAL.ADDED AG.	MILLION $	26.50	25.00	1.50	
2 EMPLOYMENT CHA.	1000 JOBS	37.88	45.00	7.13	
3 SALT CONCENTRA.	MG/L	605	615	10	
4 VAL.ADDED-ENERGY	MILLION $	2082.75	1910.63	172.11	

Figure 4.4. Table of decision maker-supplied weights for critical factor differences.

4. The component change in the constrained optima is too small.

Consistency test: The consistency test incorporated into the VODCA algorithm is a check on the position of the constrained optimum estimated from the DM provided information. If the constrained optimum does not lie in the intersection of the constraint plane and the feasible region in objective space (see Figure 4.6), the best compromise solution has been excluded from the set of remaining alternatives. The causes of this condition are either a utility function estimate which had more curvature than the actual utility function or DM provided information was inconsistent with the actual utility function.

There are several ways to check the position of the constrained optimum numerically. Perhaps the simplest test is to determine which contour of the noninferior set estimation function contains the constrained optimum. For a well-conditioned problem (the noninferior set estimation function strictly concave or convex), the noninferior surface will partition the space into two disjoint regions, a region with higher function values and a region with lower function values. If the noninferior

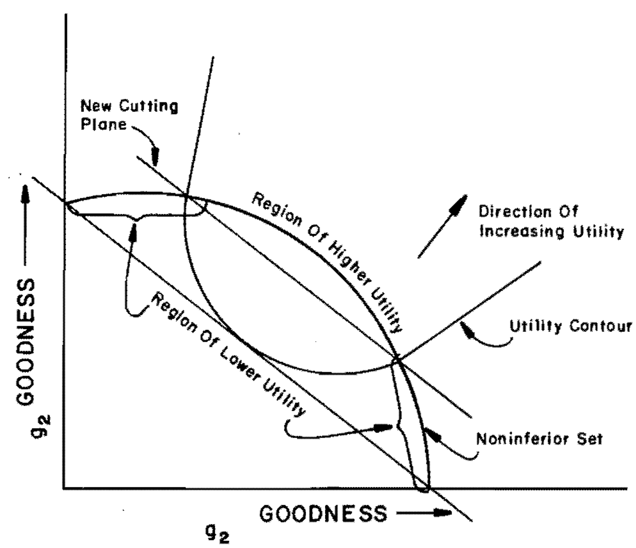


Figure 4.5. Property of cutting planes.

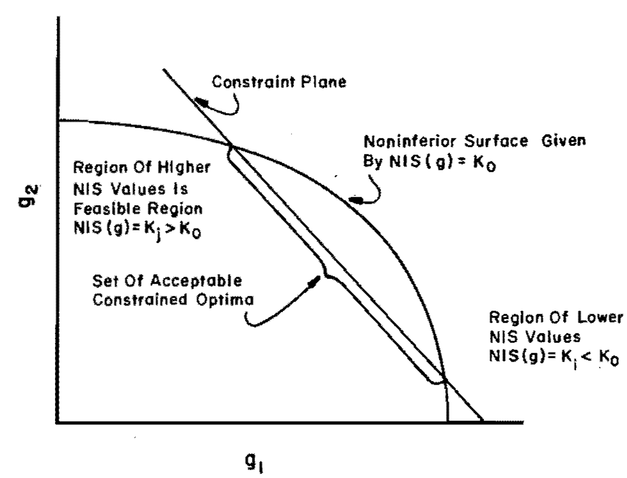


Figure 4.6. Geometry of consistency test.

set estimation function is concave and the constrained optimum lies on a contour with a higher function value, then it lies in the intersection of the feasible region and the constraint plane. On the other hand, if the constrained optimum lies on a contour of lower function values, it lies outside the feasible region. The sense of the test is reversed for convex estimation functions.

Verification test: The verification test simply confirms the estimated best compromise solution identified by the algorithm. The test consists of a DM interaction as previously described with the exception that the alternatives lie on the noninferior set near the estimated best compromise solution and include the estimated best compromise solution rather than being on a constraint plane. The DM should select the estimated best compromise solution as the preferred alternative.

4.2 APPLICATION OF VODCA TO A HYPOTHETICAL WATER RESOURCES PROBLEM

As an illustration of the solution of a MOP problem, the Dorfman-Jacoby (1969) water pollution control problem was selected for a test application of VODCA. Dorfman and Jacoby (1969) have described the hypothetical problem, so only a brief summary of the key points will be offered here.

4.2.1 The Dorfman-Jacoby Problem

As a vehicle for exploring natural resources management policy, Dorfman and Jacoby (1969) proposed a hypothetical water quality problem complete with a set of polluters, decision makers, and interested publics. For purposes of this application, the problem will be simplified as follows: 1) A single decision maker is involved, or at least, only one decision-maker's interaction with VODCA will be reported; and 2) the MOP problem will just be two-dimensional; only water-based recreation output levels and total treatment costs will be considered.

These simplifications provide the MOP problem with enough dimensions to give a preliminary test to the VODCA algorithm and avoid clouding the test with side issues of multiple publics, multiple possible river reach classifications, and so on, which were in Dorfman and Jacoby's original paper. Dorfman and Jacoby only considered dissolved oxygen and biochemical oxygen demand as water quality parameters. This work follows suit.

As illustrated in Figure 4.7, the problem concerns a 110-mile reach of the Bow River, stretching from Gordon Bridge to the state line. Three polluters discharge effluents in this reach: the Pierce-Hall Cannery at mile 10, the city of Bowville at mile 20, and the city of Plympton at mile 80. At mile 60 is Robin State Park, a significant potential source of water-based

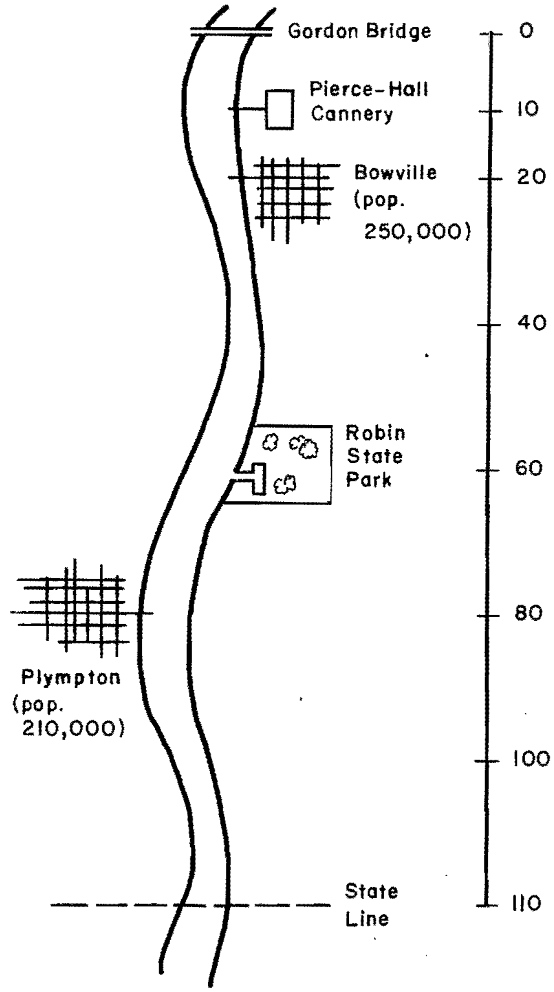


Figure 4.7. The Bow River and polluters.

recreation, if only the water in the Bow River could be brought to a sufficient quality.

Presently, the water quality in the river is very poor, allowing almost no water-based recreation. Over the potential water quality range at the state park, available water-based recreation is assumed to be a linear function of dissolved oxygen level. The only water quality constraint on this reach of the Bow River is that dissolved oxygen levels must be at least 4.0 mg/l at the state line.

All three polluters are presently using primary treatment. Estimates have been obtained for the additional annual costs of several alternatives for new waste treatment facilities. These are given in Tables 4.2 through 4.4.

4.2.2 The Dorfman-Jacoby Water Quality Model

The treatment cost-recreation noninferior surface was identified using

Table 4.2. Pierce-Hall waste treatment cost estimates (68,000 lb BOD/day).

% BOD Removed	lbs. BOD Removed	BOD Load	Additional Cost/Year $
30	20,400	47,600	0
80	54,400	13,600	8,000
90	61,200	6,800	35,000
95	64,600	3,400	95,000

Table 4.3. Bowville waste treatment cost estimates (175,700 lb BOD/day).

% BOD Removed	lbs. BOD Removed	BOD Load	Additional Cost/Year $
30	52,710	122,990	0
80	140,560	35,140	490,000
90	158,130	17,570	660,000
95	166,915	8,785	1,890,000

Table 4.4. Plympton waste treatment cost estimates (132,000 lb BOD/day).

% BOD Removed	lbs. BOD Removed	BOD Load	Additional Cost/Year $
30	39,600	92,400	0
80	105,600	26,400	410,000
90	118,800	13,200	550,000
95	125,400	6,600	1,580,000

the -constraint technique described earlier. Since the treatment costs are nonlinear functions of the design variables and recreation is a linear function of the design variables, treatment costs were chosen as the objective function in the ε-constraint formulation. The problem can be formulated as a separable programming problem using a standard software package. Formulating the multiple-objective problem as a separable ε-constraint problem and adding the functional relationships leads to:

$$\min \text{cost} = f_1(x_1) + f_2(x_2) + f_3(x_3) = g_1$$

s.t.: state line constraint:	$8.5-d_{11}x_1-d_{12}x_2-d_{13}x_3 \geq 4.0$	
DO at park:	$8.5dd_{21}x_1-d_{22}x_2$	≥ 0
DO column def. var.	$D-8.5 + d_{21}x_1+d_{22}x_2$	$= 0$
Water-based recreation	$2\,D \geq R + 4$	

where x_1, x_2, and x_3 are BOD loads from the cannery, Bowville, and Plympton, respectively; $f_1(x_1)$, $f_2(x_2)$, and $f_3(x_3)$ are the treatment costs; R is the amount of water-based recreation at the park; d_{ij}'s are Streeter-Phelps constants denoting the decrease in DO at point j caused by an increase in BOD load discharged at point i (these were supplied by Dorfman and Jacoby); D is the DO level at the park; 8.5 is the maximum DO level in the river.

Solutions on the noninferior set were found by iteratively minimizing cost while parameterizing on recreation outputs. Twenty-four points were thus obtained, as illustrated in Figure 4.8.

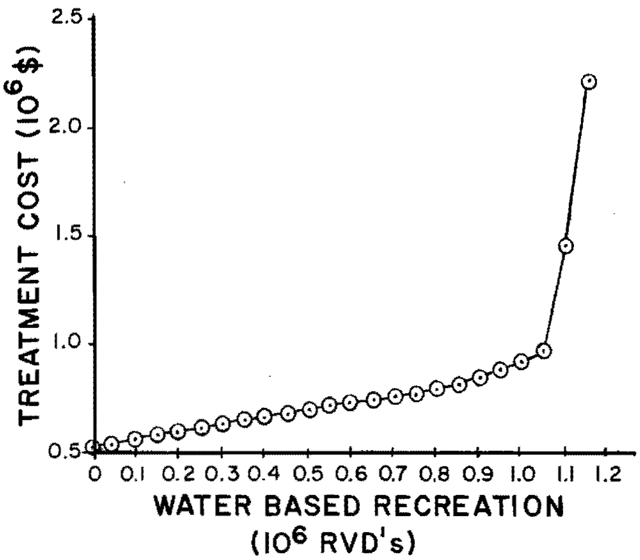


Figure 4.8. NIS points identified by the separate programming model.

4.2.3 Solution to the Dorfman-Jacoby Problem

To solve the Bow River water quality problem and identify the BCS for cost versus recreation, a computer program of the VODCA algorithm was written which would accept data about the noninferior set, the initial search planes, and the identified planar optima, which would compute estimates for the UF coefficients, and which would identify a new search plane. In addition, it would keep track of which point on the noninferior set was identified by the UF as the optimum at each iteration. For the purpose of illustrating the mathematical procedures, the program was not interfaced with the TEP algorithm. Information on planar optima was punched into the computer on a plane-by-plane basis.

As illustrated in Figure 4.9 (which has the cost axis inverted to conform more closely with the classical diagram of the noninferior set), five initial search planes were specified, along with their individual planar optima. Using this information, the algorithm found subsequent new search planes, one at a time, as numbered in Figure 4.9. As each plane was identified by VODCA, a

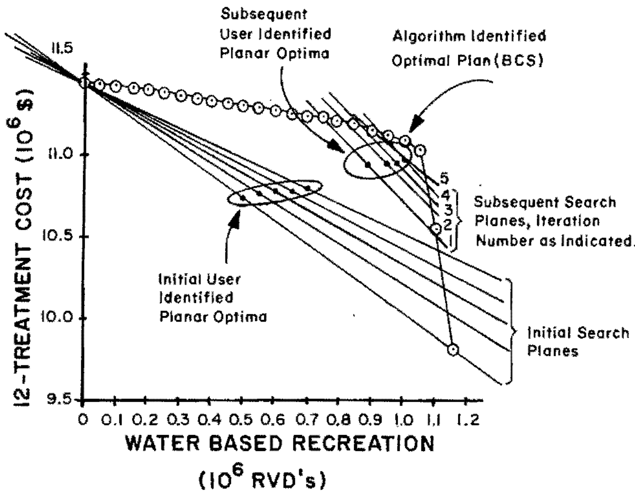


Figure 4.9. Solution to the Dorfman-Jacoby problem.

planar optimum was specified by the DM, thus allowing VODCA to hunt for a new and better plane, closing on a neighborhood of the BCS. Starting with a noninferior set of 24 points, the algorithm closed on a neighborhood of three points, in five iterations. At each iteration, point number 22 was identified as the optimal solution, or BCS. The maximum x- and y-distances between the final three points are each less than 10 percent of the initial widths of the noninferior set, probably well within the margin of error for this type of water quality model.

4.3 SUMMARY

The development of the VODCA algorithm has been presented in this chapter, including a description of how VODCA uses TEP to interact with the decision maker to obtain preference information and how the algorithm uses this information to estimate the parameters of a utility function. The Dorfman-Jacoby water quality problem was solved with VODCA as an illustration. The following chapter discusses the use of linear programming to generate an analytic expression for the noninferior surface of the application problem.

CHAPTER 5.0

A LINEAR MULTIOBJECTIVE PLANNING MODEL

5.1 PROBLEM DESCRIPTION

The eastern portion of Utah consisting of the Colorado and the Green River drainage was selected as a case study area for demonstrating the model application. This region is predominantly rural and agricultural based, with great potential for large-scale energy development. The land is rich in coal, oil, natural gas, tar sands, and shale rocks. Expansion in both underground and surface coal mining is expected in the near future. Development of synthetic crude from shale rocks using the TOSCO process is being seriously contemplated. Increasing incentives for oil and natural gas production are also being induced by favorable government policies aiming at energy independence.

Extraction of these energy resources and conversion to usable final energy outputs such as electricity or refined oil will require substantial amounts of water. In addition, increased energy production will stimulate growth in the local economy resulting in labor in-migration both in the energy sector and the service sector. This added regional growth combined with natural increases in population and economic activity will result in substantial increases in the demand for water.

Most streams in the western United States have been completely appropriated, and particularly, the Colorado system which produces the lowest amount of water per square mile drained. However, the present water uses are estimated to be slightly less than actual water availability in this area. Therefore, water for energy development could be obtained by purchases of water rights from third parties holding these rights. This could imply reduction of water in present uses, particularly in agriculture. The state and local governments have expressed repeated concerns over the destruction of the area's agricultural base and rural environment. Although economic efficiency would indicate the transfer of water from lower valued agricultural uses to higher valued energy production in a market system of water rights, social concerns will play an important role in determining the extent of such water transfers. In addition, the objective of preserving the agricultural industry and the rural atmosphere has a certain amount of intrinsic value to many of the Utah residents. Unplanned growth or the "boom" phenomenon is definitely undesirable. Yet, the job prospects, moderate growth, and planned development resulting from the exploitation of energy resources could be quite attractive to the local residents.

One further aspect of this issue is the salinity problem of the Colorado River. Increased water use in the basin could have a serious "concentrating effect" that might result in higher TDS levels downstream. Compliance with numerical standards established by EPA to protect downstream water quality could mean sacrificing part of the Upper Colorado River Basin development.

The complex development problem facing Utah can be more concretely defined in terms of the national economic development, environmental quality, regional development, and social well-being objectives outlined by the Principles and Standards. The national income criteria could be defined as the value added by the energy and agricultural sectors of the region. The environmental quality objective would be to maintain salinity levels at "reasonable" levels. The regional development criteria would be defined in terms of the total employment resulting from the future state of development. Moderate employment may be a "good" whereas excessive employment and associated "boom" may be a "bad." The social well-being objective could correspond to the preservation of agricultural base indicated by total value added in only the agricultural sector. The purpose of the model will be to generate the trade-offs between these four subobjectives.

5.2 STUDY AREA DESCRIPTION

A detailed map of Utah with energy resources and potential conversion facility locations is shown in Figure 5.1. The specific region for the case study consists of three hydrologic subunits (HSU) 7, 8, and 9 which cover the entire eastern portion of Utah. The three major HSU's were further subdivided into eight smaller units. HSU 7 is divided into five units. HSU 71 corresponds to the eastern Uintah Basin including Ashley Creek, HSU 72 to the Uintah River drainage, HSU 73 to the Lake Fork Creek drainage, HSU 74 to the Duchesne River drainage, and HSU 75 to the Strawberry River drainage. HSU 8 is divided into two units, HSU 81 corresponding to the Price River and 82 to the remainder of the Colorado River basin north and west of the Colorado River, east of Wasatch Range. HSU 9 is treated as a subarea by itself.

5.3 DESCRIPTION OF THE OPTIMIZATION FRAMEWORK

A two-sector linear programming model consisting of agriculture and probable energy activities in the basin was formulated. The four submodels contained in this formulation were the agricultural production model, the energy production model, the water resources model, and the salinity model.

The agricultural activities include production of alfalfa, small grains, corn silage, potatoes, and pasture. The net returns to agriculture were defined as the proceeds from the sale of the final outputs less the total variable costs. The relevant constraints for this submodel were the present and potential availability of different classes of irrigable lands (U.S. Department of Commerce 1974, U.S. Department of the Interior 1977) and various crop rotations. The energy submodel included production, conversion, and transportation of energy materials. Specifically, the activities considered were production of crude oil, natural gas, oil-shale, petroleum refining, surface and underground mining of coal,

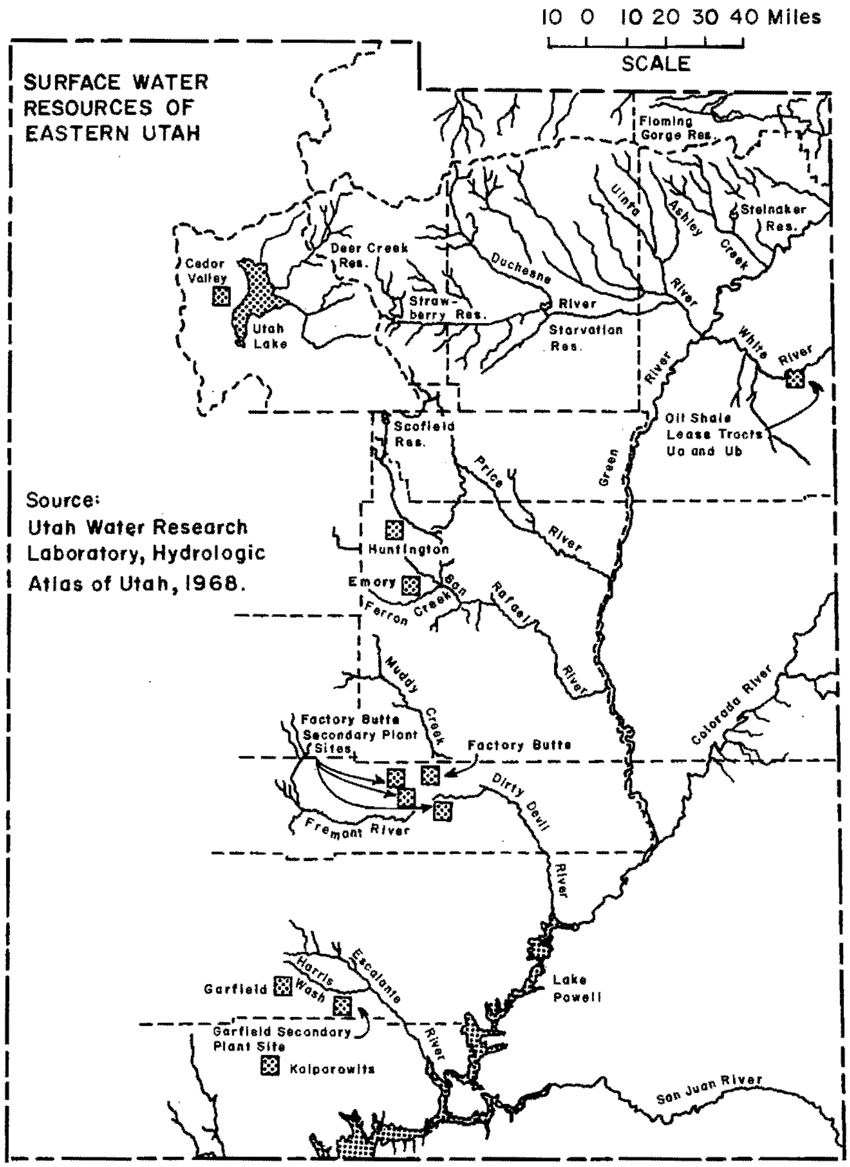


Figure 5.1. Surface water resources of eastern Utah.

coal-fired electric power generation, and coal slurry. The net returns to the energy sector were defined as the gross revenue from the sale of final energy outputs less the costs of extraction, conversion, and interregional transportation. The relevant constraints for this submodel included interregional energy flows, resource availabilities, and plant capacities of the conversion facilities.

The water resource model consisted of a set of constraints that restricted the use of water in agriculture and in energy to be less than or equal to the net availability of water in each basin less fixed requirements for other uses such as municipal, wetlands, and transbasin diversions (U.S. Water Resources Council 1971, 1976, 1977; and Christiansen 1977). Further, the total consumptive use for the state was limited by the Colorado River Basin Compact amount.

The salinity model was based on a mass-balance approach. The total natural salt inflow into any given area was first calculated. The amount of salt removed with water depletions for all uses was subtracted from this quantity. The additional salt loadings from the irrigation return flows were then added to determine the total salt contribution for each area. These were sequentially added to give the total salt proceeds from the sale of the final outputs less the total variable costs. The relevant constraints for this submodel were the present and potential availability of different classes of irrigable lands (U.S. Department of Commerce 1974, U.S. Department of the Interior 1977) and various crop rotations. The energy submodel included production, conversion, and transportation of energy materials. Specifically, the activities considered were production of crude oil, natural gas, oil-shale, petroleum refining, surface and underground mining of coal, coal-fired electric power generation, and coal slurry. The net returns to the energy sector were defined as the gross revenue from the sale of final energy outputs less the costs of extraction, conversion, and interregional transportation. The relevant constraints for this submodel included interregional energy flows, resource availabilities, and plant capacities of the conversion facilities.

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calculated. The amount of salt removed with water depletions for all uses was subtracted from this quantity. The additional salt loadings from the irrigation return flows were then added to determine the total salt contribution for each area. These were sequentially added to give the total salt loading at Lee Ferry. Both the outflow of water and salt at Lee Ferry were variables determined within the model. The constraint on the concentration of salt at any point can be set by letting the ratio of the outflow of salt to water be less than or equal to a desired level. This constraint can be expressed as a linear inequality for a given level of concentration by appropriately rearranging terms. However, there are two difficulties with this formulation. First, if the desired concentration level is changed, the coefficients of the entire equation will have to be recomputed. Second, the dual variable information corresponding to this constraint cannot be directly used. Alternatively, since the percentage change in concentration is equal to the difference in percentage changes in total dissolved solids (TDS) and the outflow of water (for small changes, the second order terms are negligible), this constraint was expressed thus as a linear inequality in changes in concentration. A more detailed description of the activity model is provided by Keith et al. (1978).

To generate trade-offs between various objectives, five objective functions based on linear relationships with the activities of the model were defined. The first objective is the net value-added in the energy sector. This is obtained by calculating the proceeds from the sale of energy products less all transportation and production costs incurred within the region. The second objective function is the net value-added in the agricultural sector. This is again calculated by defining gross revenue from the sale of all crops less the variable costs. The third objective is the sum of the first and second objectives representing the total contribution to national income. The fourth objective is the salinity level at Lee Ferry (a downstream point to the Colorado River) which indicates the water quality effects downstream. The fifth objective was the level of employment calculated as a linear function of activities used in the agriculture and energy sectors (Tables 5.1 and 5.2). Since the third objective is not independent of the first two objectives, it was not used in the computations. The next step was to derive the relationships between the four objectives. The multiobjective linear programming model was defined as follows:

$$\text{Max} \quad Z = (Z_1, Z_2, Z_3, Z_4)$$

$$\text{Subject to} \quad AX \leq b$$

$$x \geq 0$$

where Z_1, Z_2, Z_3, and Z_4 are linear functions of X.

Table 5.1. Employment levels for energy activities.

Energy Activity	Yearly Employment Per Unit of Energy Output	
	Minimum	Maximum
Underground coal mining (man/ton)	0.000073	0.000091
Crude oil (man/bbl)		0.00007
Natural gas (man/thousand cu. ft.)		0.00000004
Oil shale (man/bbl)	0.00012	0.00016
Tar sands (man/bbl)	0.00011	0.00013
Coal-fired electric plant (man/Mwh)	0.000089	0.00011
Coal slurry (man/ton)	0.000022	0.000027
Coal gasification (man/thousand cu. ft.)	0.0000071	0.0000089
Coal liquefaction (man/bbl)	0.00023	0.00028
Oil refinery (man/bbl)	0.000004	0.000005

Source: Utah State University, Colorado River Regional Assessment Study, Part II, Utah Water Research Laboratory, 1975; U.S. Department of the Interior, Bureau of Mines, Projects to Expand Fuel Sources in Western States, Information Circular 8719, 1976.

Table 5.2. Employment for agricultural activities.

Study Area	Number of Labor Work Per Acreage of Land	
	Cultivated Land	Irrigated Land
71	0.0035	0.0175
72	0.0035	0.0175
73	0.0035	0.0175
74	0.0035	0.0175
75	0.0035	0.0175
81	0.0046	0.023
82	0.0046	0.023
9	0.0123	0.062

Source: Bureau of Census, USDA, 1974.

Population multiplier: in energy sector 3
in agricultural sector 4

5.4 DATA FOR MODEL FORMULATION

The basic linear programming model constraint coefficients and the right hand side values are the same as in Keith and Turna (1978). The data for the employment objective were developed from Tables 5.1 and 5.2. The salinity objective was developed from data shown in Table 5.3. The estimated water availability for the study area for use in agriculture and energy development was 825,000 acre-feet. This is obtained from the total of Utah's share from the Colorado River and subtracting evaporation, municipal and other industrial uses, fish and wildlife, and other contractual export obligations.

5.5 MULTIOBJECTIVE LINEAR PROGRAMMING MODEL

The important aspect of a multiobjective planning problem is the determination of the set of noninferior solutions. The noninferior set is analogous to the production possibility frontier or the transformation curve (hyper surface) in the economics of general equilibrium analysis. The mathematical problem is one of determining an implicit function of the form

$$f(Z_1, Z_2 \ldots Z_n) = 0$$

where Z_1, Z_2 ... Z_n denote the n objectives. The surface f gives the maximum of any one objective achievable holding all other objectives at constant level. In general, a linear multiobjective program does not guarantee the convexity of this surface.

Two methods have been used in the literature to generate the noninferior set using linear multiobjective models. The first one uses a variety of schemes by which the objectives are weighted. A convex combination of Z_1, Z_2 ... Z_n is formed to define an objective function for the programming model. Then through parametric variation of the weights, a noninferior set is defined. The disadvantage of this procedure is that it does not generate the segment of the noninferior set where convexity conditions are violated.

The second approach is known as the constraint method. This method uses all the objectives but one as constraints. A typical scheme would be to

$$\begin{aligned} &\text{Max} && Z_1(x) \\ &\text{Subject to} && Z_i(x) \geq Z_i^* \qquad i = 2,3 \ldots n \\ & && x \in \Omega \end{aligned}$$

where Z_i^* is a stipulated level of ith objective and x are the activities of the linear programming model constrained to be in the admissible set Ω defined by the programming problem. By parametrically varying Z_i^*, all the relevant points of any arbitrarily shaped noninferior set can be generated. Due to the generality of this approach, the latter approach was used in this study.

The multiobjective problem was defined as follows:

$$\begin{aligned} &\text{Max} && Z_1(x) \\ &\text{Subject to} && Z_2(x) \leq B_2 \\ & && Z_3(x) \leq B_3 \\ & && Z_4(x) \leq B_4 \\ & && AX \leq b \\ & && x \geq 0 \end{aligned}$$

Table 5.3. Salinity data for the study area.

Study Area	River Basin	Hydrologic Study Unit	Salt Load[a] ($\times 10^3$ tons)	Water[b] Availability ($\times 10^3$ AF)	Natural[c] Salinity Concentration (tons/AF)	Return Flow Concentration (tons/AF)
71	Green River above Jensen	UG 11	1219	2942	0.41	1.20
	Ashley Creek Basin	UG 12	65	90	0.72	1.3
	White River Basin	UG 15	325	558	0.58	1.3
72, 73, 74	Duchesne River above Randlett	UG 14	394	686	0.57	1.25
75	Duchesne River above Duchesne	UG 13	147	385	0.38	1.60
81	Price River Basin	UG 16	238	108	2.15	1.0
	Other Influences		-26	-824		
	Green River above Green River		2357	3945	0.61	
82	San Rafael River	UG 18	213	176	1.21	1.25
9	San Juan above Bluff	US 7	945	1947	0.49	1.25
	Influences from the Mainstem above Cisco		5032	4812		
	Colorado above Lee Ferry	UM 14	8547	10,880	0.78	

Source: M. Leon Hyatt et al. Computer Simulation of the Hydrologic-Salinity Flow System within the Upper Colorado River Basin, Utah Water Research Laboratory, Utah State University, Logan, Utah.

[a]Summation of salt loading from measured surface inflow, ungaged surface and subsurface inflow, and natural load.

[b]Summation of water from measured surface inflow, ungaged surface and subsurface inflow + precipitation inflow with subtraction of phreatophyte consumptive use and evapotranspiration from soil.

[c]The ratio of salt load to water.

The solution procedure was implemented in two steps. First, bounds on each objective were derived. This was accomplished by optimizing each objective separately without any restrictions on other objectives. A minimum for the four objectives was determined based upon the desirable range over which each objective will be considered. These bounds are shown in Table 5.4. The second step was to determine the relationship between the four objectives. The range (max - min) of each objective (Z_2, Z_3, and Z_4) was divided into four discrete levels and an ϵ-constraint approach was used to generate the noninferior set (Cohon and Marks 1973).

The results of the parametric analyses yielded 64 possible solutions (4^3). Some of the solutions were infeasible and some others were dominated by other solutions. After eliminating these solutions, there were a total of 18 solutions on the noninferior set. A continuous approximation of the noninferior set was derived using regression analysis on the following functional specification.

$$Z_1 = a_1 + a_2 Z_2 + a_3 Z_3 + a_4 Z_4 + a_{23} Z_2 Z_3 + a_{34} Z_3 Z_4 + a_{24} Z_2 Z_4$$

Table 5.4. Bounds for the objectives.

Objective	Max.	Min.
Energy Output	$2056.45 million	$1797.18 million
Salinity	615 mg/l	605 mg/l
Employment	45,000	30,000
Agriculture Output	$26.5 million	$25 million

In the regression analyses, in addition to the 18 solutions on the noninferior set, the three optimal dual variables corresponding to each solution were also used as data for the continuous approximation.

The optimal dual variables for any solution

$$\lambda 1j = \frac{\partial Z_1}{\partial B_j} = \frac{\partial Z_1}{\partial Z_j} \quad \text{Since } B_j = Z_j$$

at the optimal point. Therefore,

$$\frac{\partial Z_1}{\partial Z_j} = a_j + \sum_k a_{jk} Z_k \qquad \text{for } j = 2, 3, 4$$

The left-hand side of this equation is the optimal dual variable value. This is expressed as a linear function of the Z_{RS} on the right hand side.

For the regression analyses, the four equations were combined so that 72 data points could be utilized. First, linear regression was used for curve-fitting. The variations in the values of Z's were too small leading to multi-collinearity problems which resulted in unstable parameter values. Therefore, ridge regression procedure was adopted with a ridge coefficient of 10^{-4}. This led to more stable parameter values with a goodness of fit of 0.99. The fitted equation for the noninferior set was

$$Z_1 = 1847.73 - 26.5338\ Z_2 + 30.3238\ Z_3 + 2.64963\ Z_4$$
$$- 1.92832\ Z_2 Z_3 - 0.0650411\ Z_2 Z_4 + 0.0387944\ Z_3 Z_4$$

The performance of this equation in terms of prediction within the relevant range of the variables was excellent. This equation was selected for use with the utility function described earlier to derive multiobjective plans interactively with the decision-maker group.

CHAPTER 6.0

APPLICATION RESULTS AND CONCLUSIONS

6.1 APPLICATION

6.1.1 Overview

As stated in the previous chapter, the objectives used in the application problem were value added for agriculture, change in employment, salt concentration at Lee Ferry, and value added in the energy sector. The analytic expression used for the noninferior surface was the one described in the previous chapter. The utility function form used in the application was that of the Stone-Geary function.

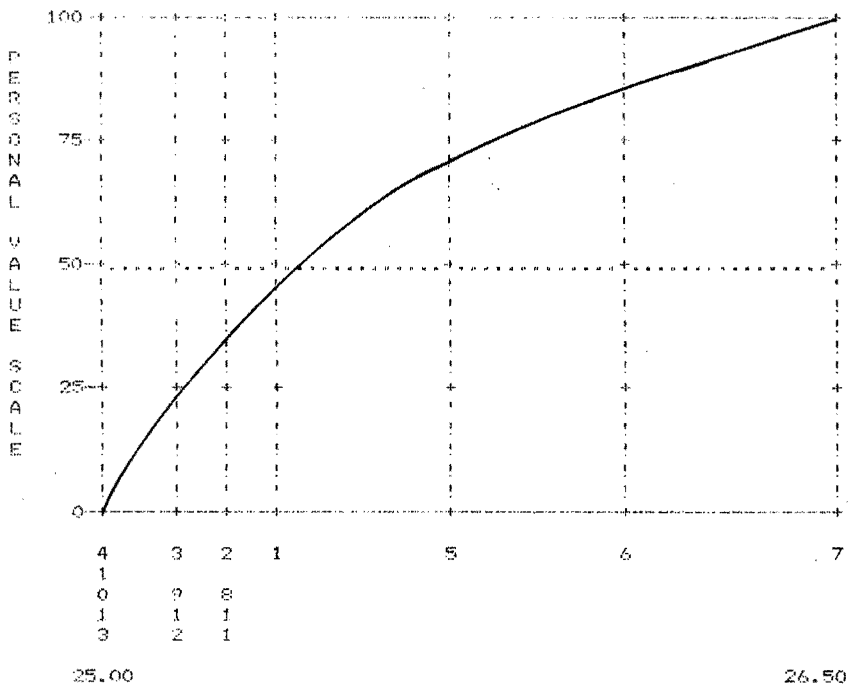
The participants in the application were planners from the Provo, Utah, office of the U.S. Bureau of Reclamation (USBR). The study is greatly indebted to these gentlemen for the donation of their time and energy in participating in the test of VODCA. It should be emphasized that the viewpoints expressed by the USBR planners in this test and demonstration of the VODCA algorithm in no way reflect USBR policy. The application was intended only as a test of the methodology by real planners for purposes of obtaining an evaluation of the utility of the methodology.

It is envisioned that under actual applications of the methodology the planning agency would involve a variety of interest groups, each of which would participate in several rounds of interaction with the VODCA algorithm. This was not possible for this pilot test of the methodology.

6.1.2 Application Results

As described in Chapter 4, the VODCA algorithm proceeds through a series of searches, where each search is represented by an examination of some of the alternatives found on a search plane which lies beneath the noninferior surface. The application of VODCA with the USBR planners required the search of four planes before convergence was reached. The first two search planes were prespecified by the project staff as part of the initial data required to run the VODCA algorithm. Interaction with the USBR planners, similar to that previously described in Chapter 4, produced the information required to enable the VODCA algorithm to estimate the Stone-Geary utility function parameters and then to identify and examine new search planes, and thus continue the VODCA iterative process. This was done until convergence was reached after the examination of the fourth search plane by the planners. The criterion for convergence used in the application was that the range in the values of each of the objectives for the final search plane must be less than one-tenth of that for the initial plane.

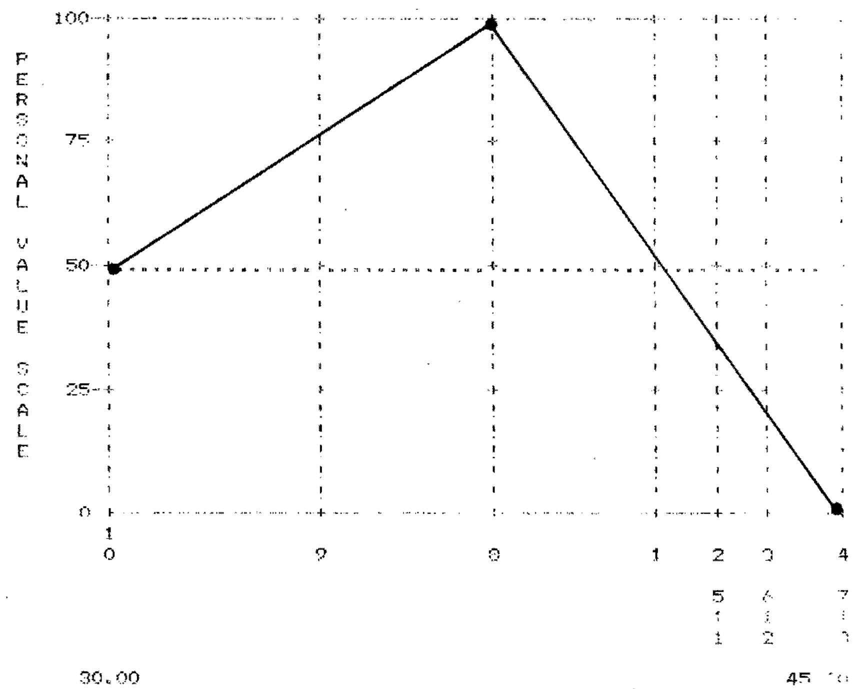
Figures 6.1a through 6.1d present the response of the planners to the VODCA algorithm's queries regarding the alternatives identified on the initial search plane. As can be seen in Figure 6.1a, the planners indicate a decreasing marginal utility for returns to agriculture over the range considered. Figure 6.1b indicates a most preferred level of approximately 38,000 jobs in terms of employment increase in eastern Utah, with increases beyond that level seen as negative. Figure 6.1c shows a linearly decreasing preference for salt concentration at Lee Ferry. Figure 6.1d shows a decreasing marginal utility curve for value added in the energy sector. Table 6.1 indicates the relative preferences of the planners over the critical ranges identified for trade-offs among the objectives. For example, the last column in Table 6.1 shows a weight of 100 for the agricultural value added factor. This means that in comparing and evaluating the alternatives from the first search plane, the difference of \$1.5 million for the value added in agriculture was judged to be the most significant of the differences across the four objectives. The weight of 50 for the salt concentration difference of 10 mg/l indicates that the planners would be indifferent between a 10 mg/l difference in salt concentration and a \$0.75 difference in agriculture value added. The weight of 20 for the difference in employment change of 7.13 thousand jobs indicates that this change is only 20 percent as important to the planners as the \$1.5 million difference in agricultural value added. Similarly, the planners indicated that the \$172 million difference for energy value added is only 30 percent as important to them as the \$1.5 million in value added for agriculture. When queried about this, the planners judged this to be a correct reflection of their viewpoints because they were concerned with preserving the historical social and cultural base of the region, and they judged that an emphasis on agriculture would do this. Large



ALTERNATIVE	FACTOR AMOUNT
1	25.38
2	25.26
3	25.15
4	25.00
5	25.71
6	26.05
7	26.50
8	25.26
9	25.15
10	25.00
11	25.26
12	25.15
13	25.00

	RANGES ON FACTORS						FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED-ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.39

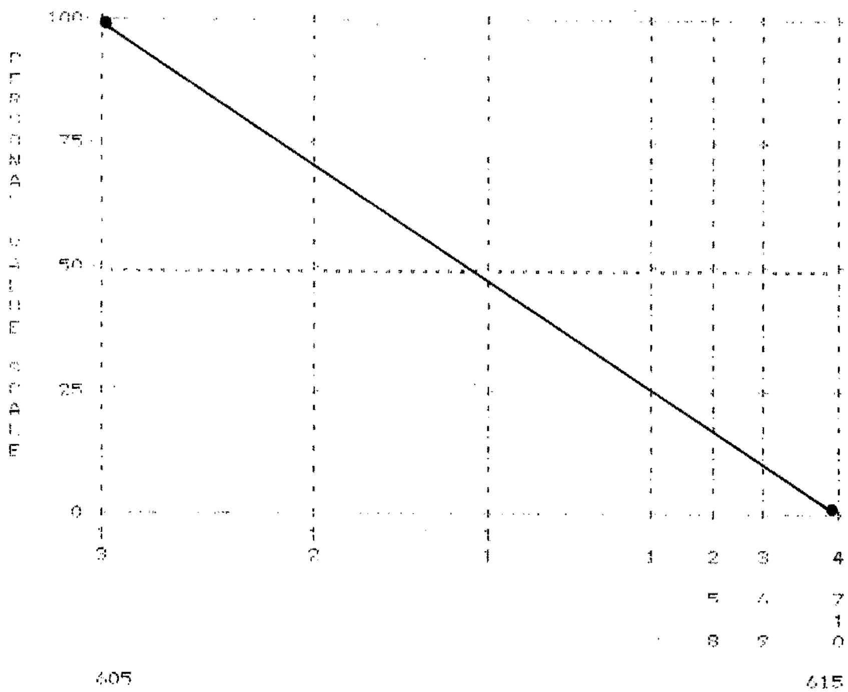
Figure 6.1a. Iteration 1.



ALTERNATIVE	FACTOR AMOUNT
1	41.25
2	42.38
3	43.50
4	45.00
5	42.38
6	43.50
7	45.00
8	37.88
9	34.50
10	30.00
11	42.38
12	43.50
13	45.00

	RANGES ON FACTORS						FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED-ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.39

Figure 6.1b. Iteration 1.



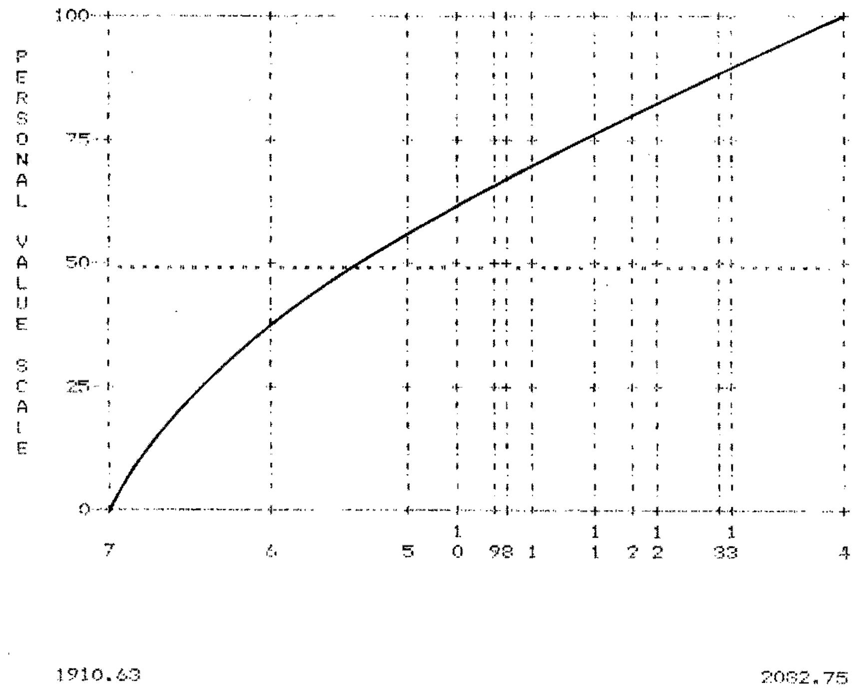
SALT CONCENTRA. (MG/L)

ALTERNATIVE	FACTOR AMOUNT
1	613
2	613
3	614
4	615
5	613
6	614
7	615
8	613
9	614
10	615
11	610
12	608
13	605

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED-ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.39

Figure 6.1c. Iteration 1.



VAL.ADDED-ENERGY (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	2010.39
2	2032.10
3	2053.80
4	2082.75
5	1980.46
6	1950.54
7	1910.63
8	2005.21
9	2000.03
10	1993.13
11	2023.79
12	2037.19
13	2055.05

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.38
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	41.25
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	613
4	VAL.ADDED-ENERGY	MILLION $	FROM	1910.63	TO	2082.75	2010.39

Figure 6.1d. Iteration 1.

developments in the energy would have socially disruptive effects on the area. This implies that even though both of these objectives are measured in terms of dollars, the planners did not view a dollar in the agricultural sector in the same light as a dollar in the energy sector.

As a final check on the results of the TEP interaction, the VODCA algorithm displays the table of weights illustrated in Table 6.2. Here the final score for each of the alternatives appears in the right hand column. The decision maker is intended to examine these weights in relation to the various objective levels of the alternatives, and verify that these accurately reflect his viewpoints. If mistakes have been made, these can be rectified before the VODCA algorithm proceeds.

Similar preference curves and trade-off weights are given for the subsequent search planes which were identified by the VODCA algorithm. These appear in Figures 6.2a through 6.2d and Tables 6.3 and 6.4 for search plane number 2, Figures 6.3a through 6.3d and Tables 6.5 and 6.6 for search plane number 3, and Figures 6.4a through 6.4d and Tables 6.7 and 6.8 for search plane number 4. Finally, Table 6.9 presents information on the location of the best compromise solution, the location of the last planar optimum, and the fact that the algorithm has at this point converged.

It should be noted that through the entire process of applying the VODCA algorithm, considerable verbal information is generated regarding the rationale behind the shapes of the various preference curves and the reasons for the weights on critical objective differences. Past applications of the TEP methodology, which VODCA uses to generate preference information about alternatives on search planes, have indicated that this verbal information can be tremendously useful in documenting the agency's position regarding the range of trade-offs among alternatives and the reasons behind the selection of a preferred alternative (see McKee and Simmons 1979, and McKee et al. 1981).

6.2 CONCLUSIONS

6.2.1 Mode of Application

The VODCA algorithm was applied to a water resources planning problem based on actual data and tested with a single group of planners/decision makers. It is envisioned that a real application of the algorithm would involve interaction with several interest groups, each of which would use VODCA to identify its own best compromise solution to the MOP problem at hand. After a best compromise solution had been identified for each interest group, a new round of applications of the VODCA algorithm would be used wherein each group would identify a new best compromise solution, taking into account information about the preferences and rationale regarding viewpoints on trade-offs expressed by other groups. By iterating through several rounds of this process, it is expected that the various interests could come to a compromise position or a globally preferred alternative. It should be noted that this iterative process might best be employed in the identification of alternatives that may be most interesting in terms of detailed consideration by the planning agency. This approach has been successfully used by the Uinta National Forest in developing its preferred forest plan (McKee et al. 1981).

6.2.2 Documentation Provided

As previously noted, application of the VODCA algorithm together with the TEP decision maker interaction mechanism, produces extensive documentation about the preferred position of a given user group and the reasons supporting that position. Similarly documentation can be provided in terms of the preferred agency position. This can be very useful in sections of planning documents dealing with the evaluation of alternatives and the reasons behind the selection of the preferred alternative. Such documentation can also be used to clearly contrast the viewpoints of various groups or the planning agency on specific trade-offs. By generating information on preference curves and the relative importance of specific trade-offs, it is possible to overlay the viewpoints of one group on top of those of another group and identify specific areas of agreement and disagreement. In this manner, areas where substantial negotiation needs to take place in order to arrive at a compromise position can be quickly identified and potential compromises examined.

6.2.3 Shortcomings

The most serious shortcoming in the application of the VODCA algorithm is the time required to successfully apply it. Successful application of VODCA requires at a minimum several hours of the user's time. Casually interested parties who are not willing to spend at least 4 or 5 hours in examining trade-offs and vocalizing opinions and preferences cannot effectively participate in the use of the VODCA algorithm.

6.2.4 Summary

In general it is felt that the VODCA algorithm is theoretically superior to many of the MOP techniques currently in the literature. In using the TEP methodology to interact with the decision maker in generating information about decision maker preferences, the VODCA methodology is distinctly superior to many MOP techniques in its mode of interaction with the decision maker, in the kind of preference information generated, and in the amount and quality of documentation provided about viewpoints regarding differences and trade-offs among alternatives.

Table 6.1. Iteration 1. Table of critical differences.

FACTORS	UNITS	MOST PREFERRED	LEAST PREFERRED	DIFFERENCE	WEIGHT
1 VAL.ADDED AG.	MILLION $	26.50	25.00	1.50	
2 EMPLOYMENT CHA.	1000 JOBS	37.88	45.00	7.13	
3 SALT CONCENTRA.	MG/L	605	615	10	
4 VAL.ADDED ENERGY	MILLION $	2082.75	1910.63	172.11	

Table 6.2. Iteration 1. Summary of TEP findings.

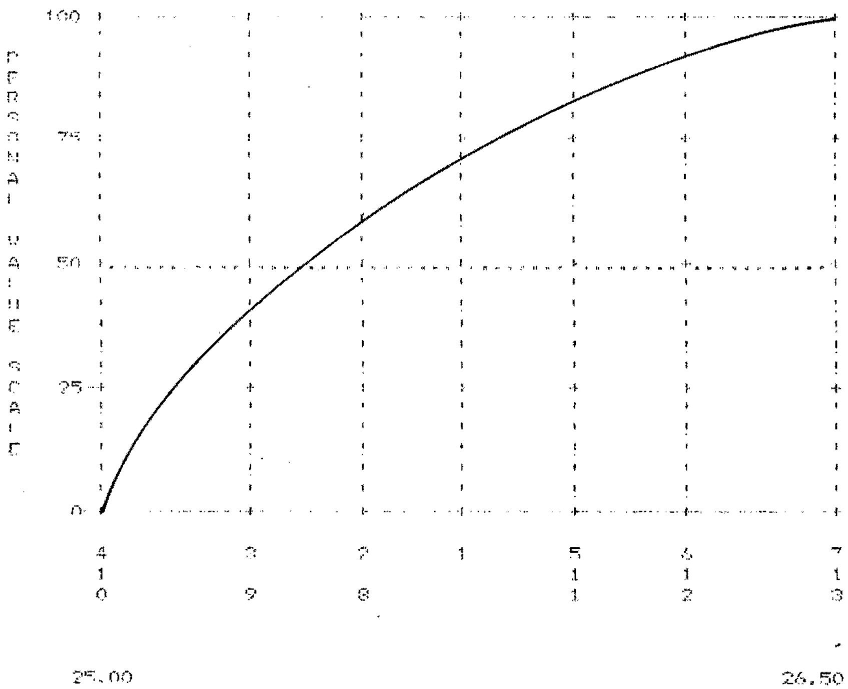
ALT:	FACTORS 1	2	3	4	TOTAL WT
1	25.38	41.25	612.50	2010.39	
	45.00	13.00	11.50	21.00	90.50
2	25.26	42.38	613.25	2032.10	
	35.00	9.00	7.50	24.00	75.50
3	25.15	43.50	614.00	2053.80	
	20.00	6.00	5.00	26.40	57.40
4	25.00	45.00	615.00	2082.75	
	0.00	0.00	0.00	30.00	30.00
5	25.71	42.38	613.25	1980.46	
	70.00	9.00	7.50	16.50	103.00
6	26.05	43.50	614.00	1950.54	
	85.00	6.00	3.00	1.80	95.80
7	26.50	45.00	615.00	1910.63	
	100.00	0.00	0.00	0.00	100.00
8	25.26	37.88	613.25	2005.21	
	35.00	20.00	7.50	19.50	82.00
9	25.15	34.50	614.00	2000.03	
	20.00	14.00	4.50	18.90	57.40
10	25.00	30.00	615.00	1993.13	
	0.00	10.00	0.00	18.00	28.00
11	25.26	42.38	610.25	2023.79	
	35.00	9.00	22.50	22.80	89.30
12	25.15	43.50	608.00	2037.19	
	20.00	6.00	35.00	25.50	86.50
13	25.00	45.00	605.00	2055.05	
	0.00	0.00	50.00	27.00	77.00

Table 6.3. Iteration 2. Table of critical differences.

FACTORS	UNITS	MOST PREFERRED	LEAST PREFERRED	DIFFERENCE	WEIGHT
1 VAL.ADDED-AG.	MILLION $	26.50	25.00	1.50	
2 EMPLOYMENT CHA.	1000 JOBS	37.50	45.00	7.50	
3 SALT CONCENTRA.	MG/L	605	615	10	
4 VAL.ADDED-ENERGY	MILLION $	2082.75	1864.40	218.34	

Table 6.4. Iteration 2. Summary of TEP findings.

	FACTORS				
ALT:	1	2	3	4	TOTAL WT
1	25.75 70.00	37.50 30.00	610.00 25.00	1950.55 24.00	149.00
2	25.53 60.00	39.75 21.00	611.50 18.50	1990.21 30.00	129.50
3	25.30 37.00	42.00 11.10	613.00 10.00	2029.87 34.80	92.90
4	25.00 0.00	45.00 0.00	615.00 0.00	2082.75 40.00	40.00
5	25.97 85.00	35.25 24.00	611.50 18.50	1924.70 18.80	146.30
6	26.20 90.00	33.00 21.00	613.00 10.00	1898.86 12.00	133.00
7	26.50 100.00	30.00 15.00	615.00 0.00	1864.40 0.00	115.00
8	25.53 60.00	35.25 24.00	608.50 33.50	1956.76 26.00	143.50
9	25.30 37.00	33.00 21.00	607.00 38.50	1962.97 26.80	123.30
10	25.00 0.00	30.00 15.00	605.00 50.00	1971.26 28.00	93.00
11	25.97 85.00	39.75 21.00	608.50 33.50	1930.52 20.80	160.30
12	26.20 90.00	42.00 11.10	607.00 38.50	1910.49 15.20	154.80
13	26.50 100.00	45.00 0.00	605.00 50.00	1883.79 8.00	158.00



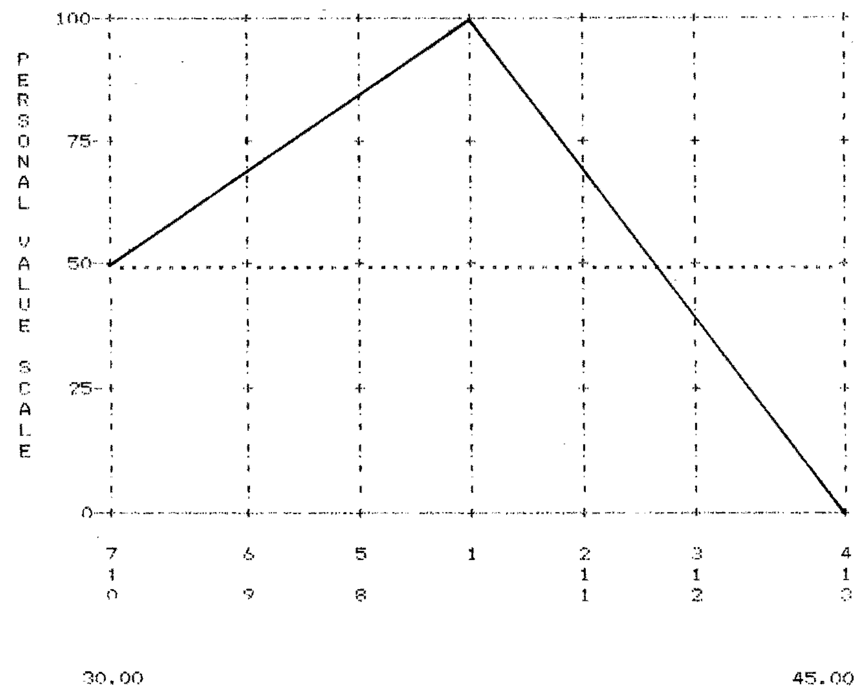
VAL.ADDED-AG. (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	25.75
2	25.53
3	25.30
4	25.00
5	25.97
6	26.20
7	26.50
8	25.53
9	25.30
10	25.00
11	25.97
12	26.20
13	26.50

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.75
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	37.50
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	610
4	VAL.ADDED-ENERGY	MILLION $	FROM	1864.40	TO	2082.75	1950.55

Figure 6.2a. Iteration 2.



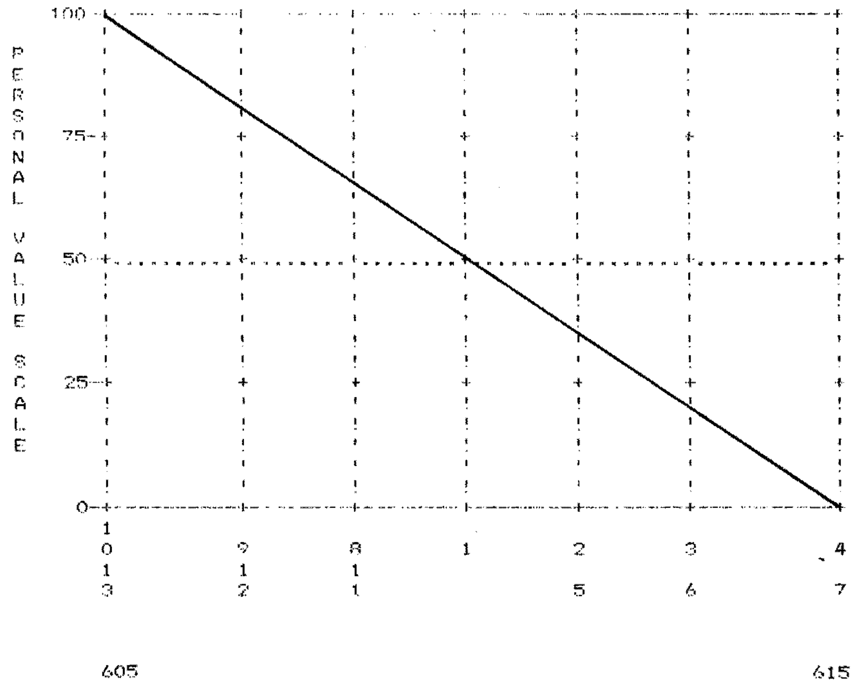
EMPLOYMENT CHA. (1000 JOBS)

ALTERNATIVE	FACTOR AMOUNT
1	37.50
2	39.75
3	42.00
4	45.00
5	35.25
6	33.00
7	30.00
8	35.25
9	33.00
10	30.00
11	39.75
12	42.00
13	45.00

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.75
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	37.50
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	610
4	VAL.ADDED-ENERGY	MILLION $	FROM	1864.40	TO	2082.75	1950.55

Figure 6.2b. Iteration 2.



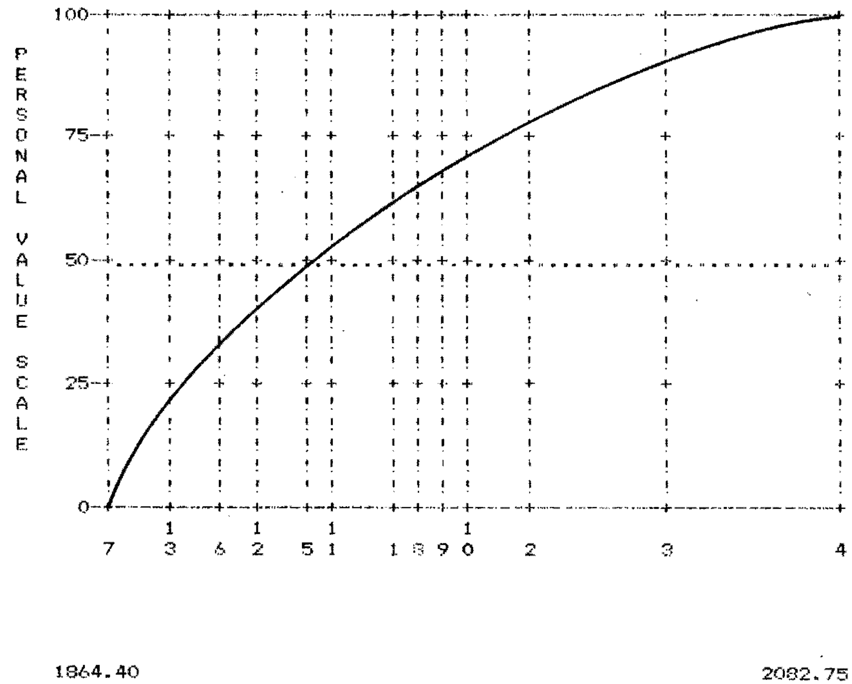
SALT CONCENTRA. (MG/L)

ALTERNATIVE	FACTOR AMOUNT
1	610
2	612
3	613
4	615
5	612
6	613
7	615
8	609
9	607
10	605
11	609
12	607
13	605

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.75
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	37.50
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	610
4	VAL.ADDED ENERGY	MILLION $	FROM	1864.40	TO	2082.75	1950.55

Figure 6.2c. Iteration 2.



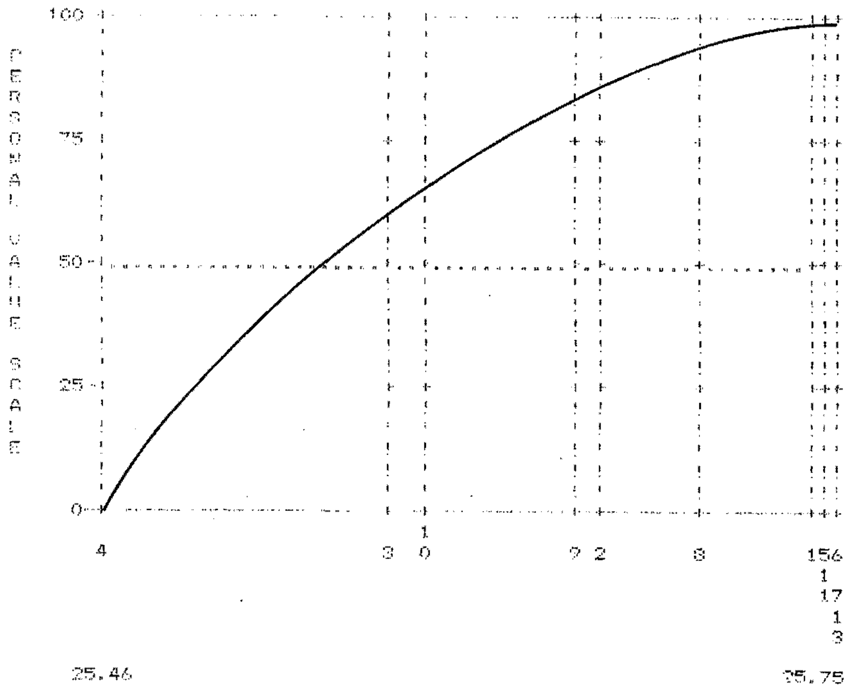
VAL.ADDED-ENERGY (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	1950.55
2	1990.21
3	2029.87
4	2082.75
5	1924.70
6	1898.86
7	1864.40
8	1956.76
9	1962.97
10	1971.26
11	1930.52
12	1910.49
13	1883.79

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.00	TO	26.50	25.75
2	EMPLOYMENT CHA.	1000 JOBS	FROM	30.00	TO	45.00	37.50
3	SALT CONCENTRA.	MG/L	FROM	605	TO	615	610
4	VAL.ADDED-ENERGY	MILLION $	FROM	1864.40	TO	2082.75	1950.55

Figure 6.2d. Iteration 2.



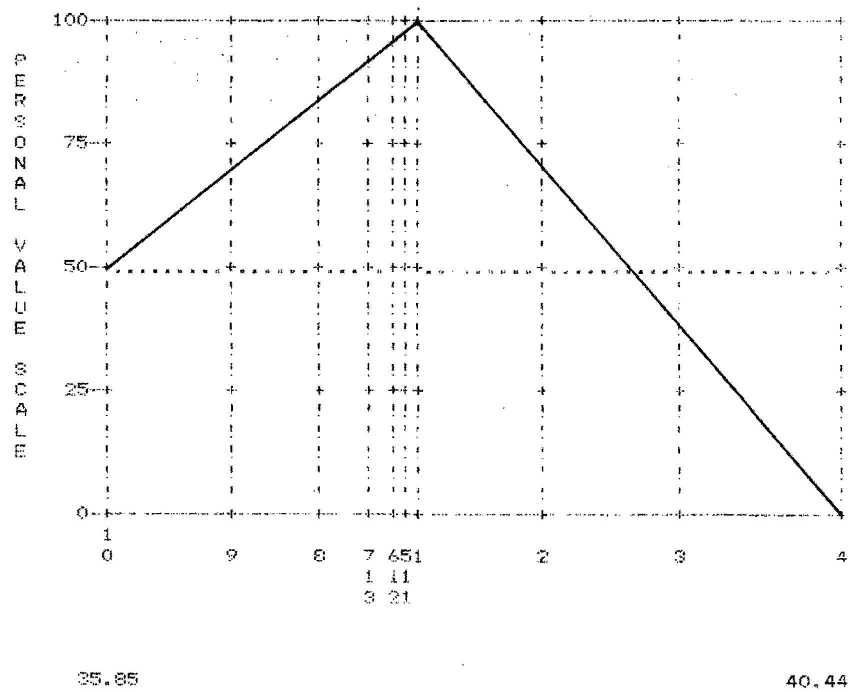
VAL.ADDED-AG. (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	25.74
2	25.66
3	25.57
4	25.46
5	25.74
6	25.75
7	25.75
8	25.69
9	25.65
10	25.59
11	25.74
12	25.75
13	25.75

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.46	TO	25.75	25.74
2	EMPLOYMENT CHA.	1000 JOBS	FROM	35.85	TO	40.44	37.80
3	SALT CONCENTRA.	MG/L	FROM	609	TO	612	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.48	TO	1999.33	1950.60

Figure 6.3a. Iteration 3.



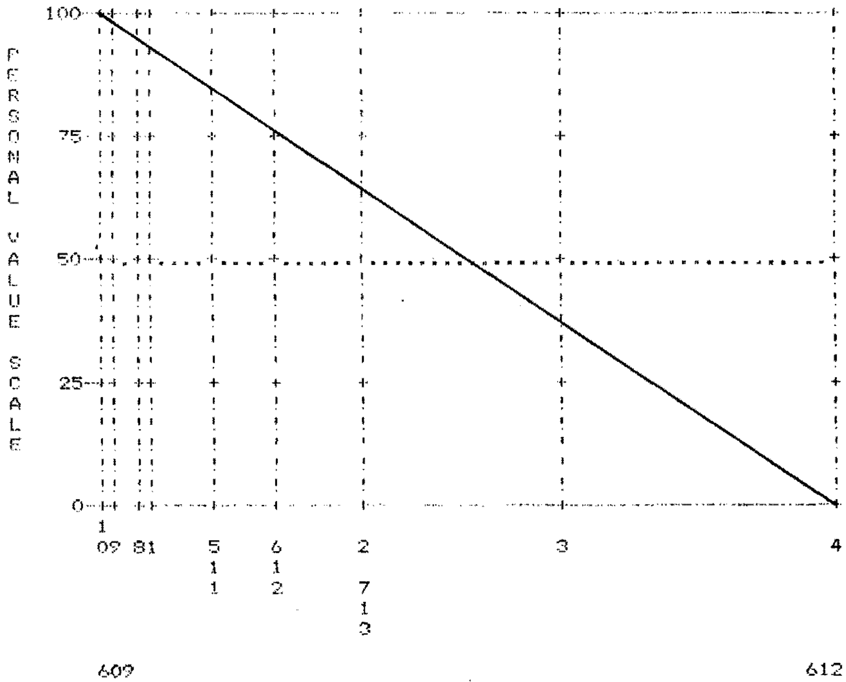
EMPLOYMENT CHA. (1000 JOBS)

ALTERNATIVE	FACTOR AMOUNT
1	37.80
2	38.59
3	39.38
4	40.44
5	37.71
6	37.62
7	37.49
8	37.22
9	36.63
10	35.85
11	37.72
12	37.63
13	37.51

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.46	TO	25.75	25.74
2	EMPLOYMENT CHA.	1000 JOBS	FROM	35.85	TO	40.44	37.80
3	SALT CONCENTRA.	MG/L	FROM	609	TO	612	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.48	TO	1999.33	1950.60

Figure 6.3b. Iteration 3.

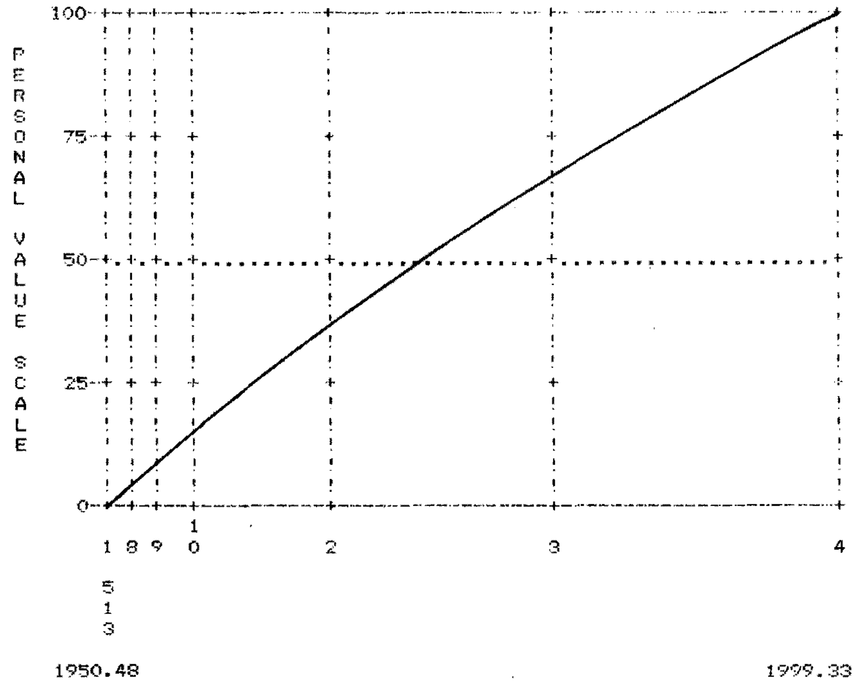


SALT CONCENTRA. (MG/L)

ALTERNATIVE	FACTOR AMOUNT
1	609
2	610
3	611
4	612
5	609
6	610
7	610
8	609
9	609
10	609
11	609
12	610
13	610

	RANGES ON FACTORS						FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.46	TO	25.75	25.74
2	EMPLOYMENT CHA.	1000 JOBS	FROM	35.85	TO	40.44	37.80
3	SALT CONCENTRA.	MG/L	FROM	609	TO	612	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.48	TO	1999.33	1950.60

Figure 6.3c. Iteration 3.

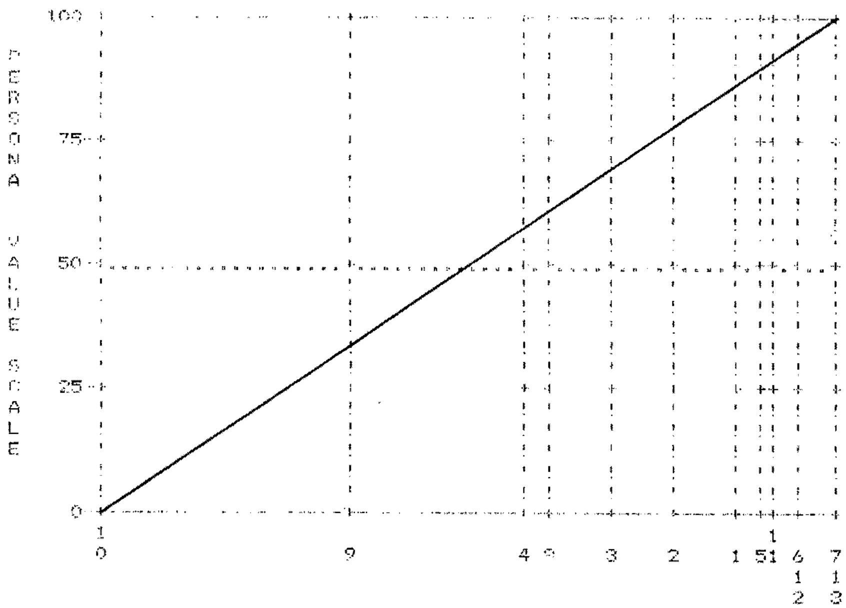


VAL.ADDED-ENERGY (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	1950.60
2	1965.22
3	1979.84
4	1999.33
5	1950.56
6	1950.53
7	1950.48
8	1952.45
9	1954.31
10	1956.78
11	1950.56
12	1950.53
13	1950.49

	RANGES ON FACTORS						FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.46	TO	25.75	25.74
2	EMPLOYMENT CHA.	1000 JOBS	FROM	35.85	TO	40.44	37.80
3	SALT CONCENTRA.	MG/L	FROM	609	TO	612	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.48	TO	1999.33	1950.60

Figure 6.3d. Iteration 3.



25.69 25.74

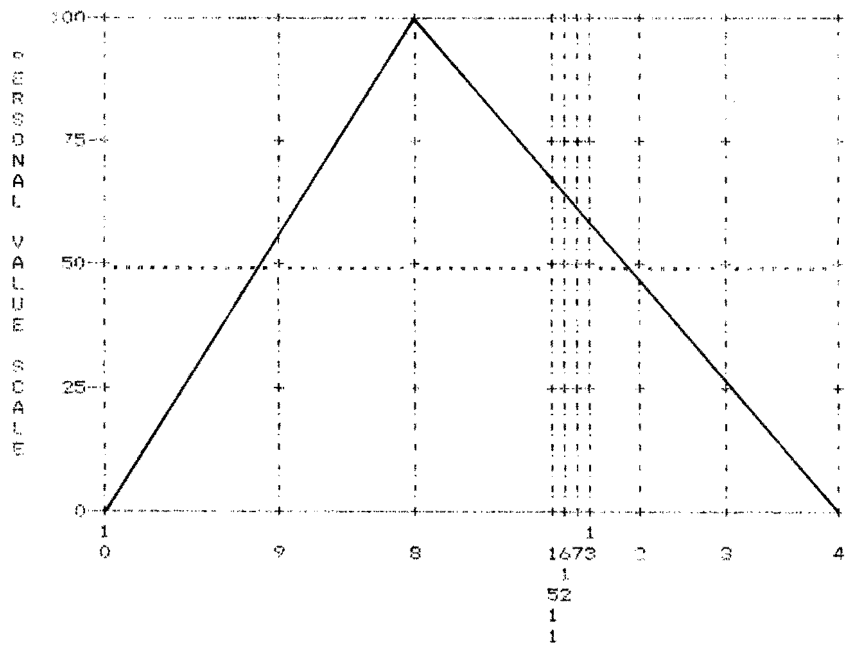
VAL.ADDED AG. (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	25.73
2	25.73
3	25.73
4	25.72
5	25.74
6	25.74
7	25.74
8	25.72
9	25.71
10	25.69
11	25.74
12	25.74
13	25.74

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED AG.	MILLION $	FROM	25.69	TO	25.74	25.73
2	EMPLOYMENT CHA.	1000 JOBS	FROM	37.27	TO	37.93	37.67
3	SALT CONCENTRA.	MG/L	FROM	609	TO	609	609
4	VAL.ADDED ENERGY	MILLION $	FROM	1950.25	TO	1953.52	1950.25

Figure 6.4a. Iteration 4.



37.27 37.93

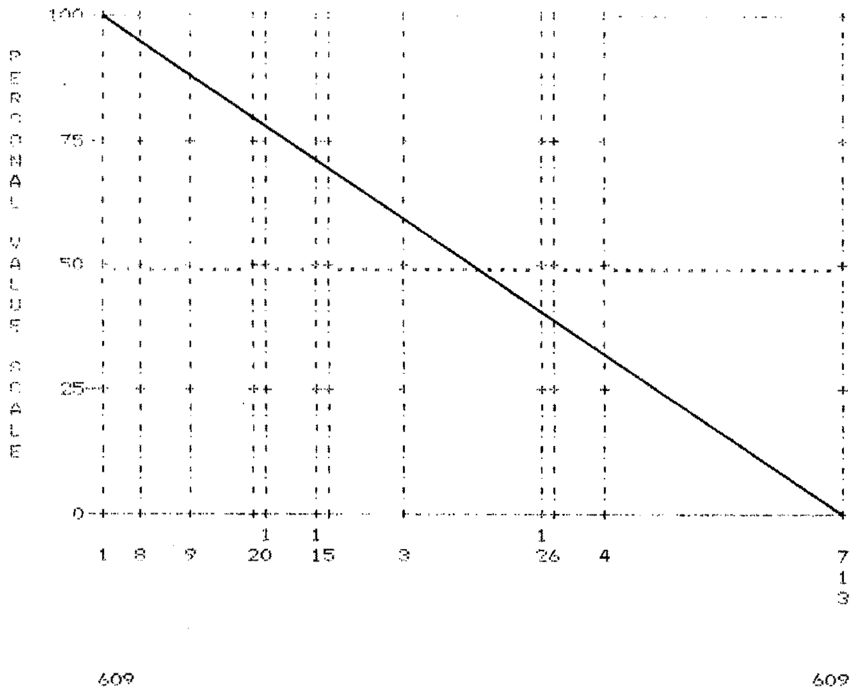
EMPLOYMENT CHA. (1000 JOBS)

ALTERNATIVE	FACTOR AMOUNT
1	37.67
2	37.75
3	37.83
4	37.93
5	37.68
6	37.69
7	37.70
8	37.55
9	37.43
10	37.27
11	37.68
12	37.69
13	37.70

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.69	TO	25.74	25.73
2	EMPLOYMENT CHA.	1000 JOBS	FROM	37.27	TO	37.93	37.67
3	SALT CONCENTRA.	MG/L	FROM	609	TO	609	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.25	TO	1953.52	1950.25

Figure 6.4b. Iteration 4.



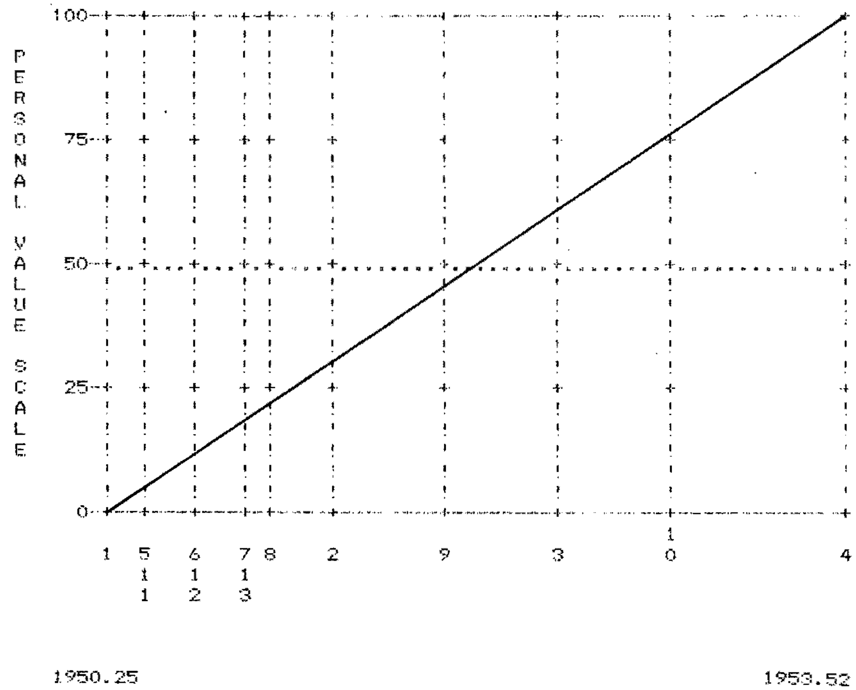
SALT CONCENTRA. (MG/L)

ALTERNATIVE	FACTOR AMOUNT
1	609
2	609
3	609
4	609
5	609
6	609
7	609
8	609
9	609
10	609
11	609
12	609
13	609

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.69	TO	25.74	25.73
2	EMPLOYMENT CHA.	1000 JOBS	FROM	37.27	TO	37.93	37.67
3	SALT CONCENTRA.	MG/L	FROM	609	TO	609	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.25	TO	1953.52	1950.25

Figure 6.4c. Iteration 4.



VAL.ADDED-ENERGY (MILLION $)

ALTERNATIVE	FACTOR AMOUNT
1	1950.25
2	1951.23
3	1952.21
4	1953.52
5	1950.44
6	1950.64
7	1950.90
8	1951.00
9	1951.75
10	1952.75
11	1950.44
12	1950.64
13	1950.90

RANGES ON FACTORS

							FOCUS
1	VAL.ADDED-AG.	MILLION $	FROM	25.69	TO	25.74	25.73
2	EMPLOYMENT CHA.	1000 JOBS	FROM	37.27	TO	37.93	37.67
3	SALT CONCENTRA.	MG/L	FROM	609	TO	609	609
4	VAL.ADDED-ENERGY	MILLION $	FROM	1950.25	TO	1953.52	1950.25

Figure 6.4d. Iteration 4.

Table 6.5. Iteration 3. Table of critical differences.

FACTORS	UNITS	MOST PREFERRED	LEAST PREFERRED	DIFFERENCE	WEIGHT
1 VAL.ADDED-AG.	MILLION $	25.75	25.46	0.29	
2 EMPLOYMENT CHA.	1000 JOBS	37.80	40.44	2.63	
3 SALT CONCENTRA.	MG/L	609	612	3	
4 VAL.ADDED-ENERGY	MILLION $	1999.33	1950.60	48.73	

Table 6.6. Iteration 3. Summary of TEP findings.

	FACTORS				
ALT:	1	2	3	4	TOTAL WT
1	25.74 98.00	37.80 40.00	609.14 74.40	1950.60 0.00	212.40
2	25.66 85.00	38.59 29.60	609.98 54.40	1965.22 16.00	185.00
3	25.57 56.00	39.38 16.00	610.83 30.40	1979.84 28.00	130.40
4	25.46 0.00	40.44 0.00	611.96 0.00	1999.33 40.00	40.00
5	25.74 99.00	37.71 39.20	609.40 68.80	1950.56 0.00	207.00
6	25.75 100.00	37.62 38.40	609.66 60.00	1950.53 0.00	198.40
7	25.75 100.00	37.49 36.40	610.01 54.40	1950.48 0.00	190.80
8	25.69 90.00	37.22 34.40	609.07 76.00	1952.45 2.00	202.40
9	25.65 82.00	36.63 28.00	609.00 78.40	1954.31 3.20	191.60
10	25.59 68.00	35.85 20.00	608.90 80.00	1956.78 6.00	174.00
11	25.74 99.00	37.72 39.20	609.39 68.80	1950.56 0.00	207.00
12	25.75 100.00	37.63 38.40	609.65 60.00	1950.53 0.00	198.40
13	25.75 100.00	37.51 36.40	609.99 54.40	1950.49 0.00	190.80

Table 6.7. Iteration 4. Table of critical differences.

FACTORS	UNITS	MOST PREFERRED	LEAST PREFERRED	DIFFERENCE	WEIGHT
1 VAL.ADDED-AG.	MILLION $	25.74	25.69	0.05	
2 EMPLOYMENT CHA.	1000 JOBS	37.55	37.93	0.39	
3 SALT CONCENTRA.	MG/L	609	609	0	
4 VAL.ADDED-ENERGY	MILLION $	1953.52	1950.25	3.27	

Table 6.8. Iteration 4. Summary of TEP findings.

	FACTORS				
ALT:	1	2	3	4	TOTAL WT
1	25.73	37.67	608.95	1950.25	
	87.00	22.44	0.00	0.00	109.44
2	25.73	37.75	609.04	1951.23	
	77.00	14.85	0.00	6.00	97.85
3	25.73	37.83	609.13	1952.21	
	70.00	6.93	0.00	13.40	90.33
4	25.72	37.93	609.25	1953.52	
	58.00	0.00	0.00	20.00	78.00
5	25.74	37.68	609.08	1950.44	
	90.00	22.44	0.00	1.00	113.44
6	25.74	37.69	609.22	1950.64	
	95.00	21.45	0.00	2.40	118.85
7	25.74	37.70	609.40	1950.90	
	100.00	20.46	0.00	3.60	124.06
8	25.72	37.55	608.98	1951.00	
	66.00	33.00	0.00	4.00	103.00
9	25.71	37.43	609.01	1951.75	
	34.00	16.50	0.00	9.00	59.50
10	25.69	37.27	609.04	1952.75	
	0.00	0.00	0.00	15.00	15.00
11	25.74	37.68	609.08	1950.44	
	91.00	22.44	0.00	1.00	114.44
12	25.74	37.69	609.22	1950.64	
	95.00	21.45	0.00	2.40	118.85
13	25.74	37.70	609.39	1950.90	
	100.00	18.15	0.00	3.60	121.75

Table 6.9. Iteration 4.

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PRESENT ESTIMATED LOCATION OF BCS:



  FACTOR # 1  (VAL.ADDED-AG.     ):      25.73
  FACTOR # 2  (EMPLOYMENT CHA.   ):      37.67
  FACTOR # 3  (SALT CONCENTRA.   ):        609
  FACTOR # 4  (VAL.ADDED-ENERGY):     1950.25

CONVERGENCE DATA:
  FACTOR # 1  (VAL.ADDED-AG.     ) HAS CONVERGED.
  FACTOR # 2  (EMPLOYMENT CHA.   ) HAS CONVERGED.
  FACTOR # 3  (SALT CONCENTRA.   ) HAS CONVERGED.
  FACTOR # 4  (VAL.ADDED-ENERGY) HAS CONVERGED.
CONVERGENCE FLAG IS SET.  NOW CALLING FOR VERIFICATION.
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