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ALTERNATIVES IN FACILITY SITING STUDIES
Abstract Approved: Redacted for Privacy
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Facility location studies involve the selection of a preferred course of action from an array of multiattributed alternatives. The factors affecting this selection are defined in both quantifiable and qualifiable terms. The former comprises primarily monetary or operational data, and the latter consists of nonmonetary and environmental parameters; where the term "environmental" encompasses all forms of ecological and societal influences at the proposed locations.

Most current techniques developed for multiattributed analysis are strictly mathematical in nature and do not adequately consider the possible effect of subjective variables. Additionally, those procedures which do include techniques for evaluating subjective factors usually employ data in the form of point estimates and make no provisions for the incorporation of probabilistic variability. Recently increasing environmental concern and the high degree of uncertainty which currently exists in construction and operating cost estimates have limited the usefulness of models which are not designed to incorporate such factors.

The intent of this paper is to present a detailed procedure to overcome the weaknesses of currently available comparison models. It does so by examining existing models and then developing a methodology based on extensions to the linear additive weighting model. Methods of obtaining relative factor importance are surveyed and weightings are obtained through the utilization of procedures based on the partial paired comparison technique.

Significant improvements over conventional comparison models include the facility for evaluating subjective input through the application of utility or impact scaling functions. These functions are the bases for transforming probabilistic site-design performance estimates into relative impact measurements. Aggregate potential environmental impact profiles are next developed for each alternative by Monte Carlo simulation techniques. The resulting qualitative ratings are then combined with qualitative data by means of a relative importance ratio to obtain a single measure of an alternative's desirability. Finally, a method for determining the sensitivity of the selection procedure is illustrated through simulation.

The development and discussion of the evalution procedure is paralleled by an example problem based in part on data collected during siting studies for a large electrical generating facility. Examples of computer input data forms and simulation results are provided along with FORTRAN IV program listings.

An Integrated Approach to the Evaluation of Multiattributed Alternatives in Facility Siting Studies

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AN INTEGRATED APPROACH TO THE EVALUATION OF MULTIATTRIBUTED ALTERNATIVES IN FACILITY SITING STUDIES

I. INTRODUCTION

Plant location problems have been studied for many years. Undoubtedly, rulers of early civilizations were faced with decisions as to where their trade goods should be produced. The consolidation of raw materials and energy supplies has long been a problem. Even when the primary energy source was manpower, the elemental fuel for that source was food, which was often difficult to obtain in sufficient quantities at the places where necessary raw materials and ores were available.

The industrial revolution brought forth an age where manufacturing became much more energy dependent. Early areas of industrial growth were centered in locations where adequate water power was available and easily tapped. With the advent of the steam engine, industrial development became less dependent upon the immediate availability of naturally occurring water resources and more locationally oriented toward supplies of satisfactory fuels. The rapid development of the steam engine as a prime mover in both steamboats and railway locomotives also permitted the transport of raw materials and finished goods over distances which were economically unattractive just a few years earlier.

The introduction of electrical power as an easily transported source of energy permitted even greater freedom in the selection of economically attractive manufacturing sites. Large scale natural gas and petroleum pipeline networks and the development of a massive highway system for the distribution of other fuels have further accelerated industrial development in many areas of the United States. Throughout this era of national development, there was a clear if sometimes undeclared public policy preference for the initiators of economically productive actions. It was assumed that industrial growth and development were simply desirable, and little legal or political interference was expected. This assumption of desirability was particularly strong in the area of energy development and supply.

In this atmosphere of growth encouragement, the analysis of where to locate manufacturing or energy supply facilities was based almost entirely on economic considerations. For over 100 years, formal studies concerning the economic attractiveness of alternatives have been published (Farr, 1876). Various methods have been developed for the evaluation of siting alternatives through the analysis of direct economic factors. Generally, these efforts have involved the consideration of direct labor and material costs, the availability of raw materials, transportation and energy costs, and the accessibility of a potential market (Holmes, 1930; Greenhut, 1956; Reed, 1967; Brown and Gibson, 1971).

The importance of accurate facility location studies goes without saying. Mistakes in this area, if not financially permanent, are extremely costly to rectify. The continuance of profitable operation often depends on the correct decision resulting from such siting studies.

The significance of direct cost studies cannot be overstated. However, in the past few years, increased concern for the environment and a growing public awareness of the nonmonetary costs associated with unlimited growth have effected a significant change in the concept of such studies. The inclusion of nonmonetary or indirect costs or impacts in siting studies involving large scale construction activities has become a legal necessity. Federal legislations, starting with the Corps of

Engineers administered Refuse Act of 1899 and continuing through various revisions of the National Environmental Policy Act (NEPA) of 1969, have placed increasing emphasis on the importance of nonmonetary considerations.

State legislatures have also been very active in the area of developing regulations affecting the construction and operation of large scale facilities. This is particularly true in the area of preconstruction certification of new electric power generating plants. This shift towards environmental priorities often places the burden upon industry to come forward with evidence justifying its proposed action and demonstrating that it will not unduly disturb the natural environment. These factors confirm the need for the inclusion of additional nonmonetary data in the site selection process.

This thesis is concerned with the problem of evaluating various alternative sites for the construction of large scale industrial complexes. While the methodology developed is primarily oriented towards the choice of sites for the production of electric power, the procedures described should be applicable to the analysis of nonmonetary factors affecting most location decisions. It is true that the decision parameters presented to a public utility searching for an optimum power production site are somewhat different from those in private industry. However, both types of organizations face the problem of attempting to evaluate various so-called "intangible" factors. It is toward those areas of evaluation that this research is oriented.

The complexity of electric power generation systems makes it necessary to simplify as much as is practical the problem being considered. The present paper is concerned with developing a method for evaluating relevant nonmonetary attributes involved in power plant site-design decisions and then integrating with direct expense data to determine an aggregate measure of desirability. In order to keep the problem within manageable size, certain limiting assumptions have been applied. The most important of these is perhaps that the social need for additional regional generating capacity has been adequately demonstrated. Sociopolitical problems involving overall electric power requirements and the multiple implications therein are beyond the scope of this work. However, it is possible that some of the evaluation methods presented may prove of use in a study involving such considerations.

Additional assumptions are made in the areas of generating system reliability and the equal ability for each of the site-design alternatives to meet projected power loads. For the particular set of alternatives used in the illustrative example, it is also assumed that each of the site-design combinations has approximately the same chance of experiencing a low probability-high consequent event. That is, the probability of a catastrophic event occurring is equal for each of the alternatives being considered. These events could result from either natural phenomena such as earthquakes, or human actions such as massive sabotage or the crash of a large aircraft into the facility. Since equal risk is assumed for each alternative, no single site is favored. Therefore, these factors do not appear in the illustrative example. When difference between alternatives do exist, they could be incorporated into the evaluation procedure if adequate descriptive data are available.

The resulting product of this research is a procedural methodology which permits the incorporation of qualitative parameters in the site evaluation process. The primary area of interest concerns the development of techniques to evaluate these nonmonetary attributes on a relative basis, and the supporting assumption is made that it is possible to obtain adequate estimates of the direct or monetary costs for each of the potential sites being considered. In order to accomplish this integration of quantitative and qualitative data the following procedure will be followed:

1. Develop direct cost estimates for the construction, operation, decommission, and salvage of the generating facility and associated ancillary equipment.
2. Identify relevant environmental factors suitable for describing the impact of the facility in nonmonetary assignable areas. These factors should be defined in sufficient detail to exclude descriptive overlap and eliminate interdependencies.
3. Determine relative importance weightings for each of the nonmonetary factors.
4. Subdivide these factors into subfactors for which directly measurable criteria can be identified.
5. Develop dimensionless scales of utility or value for each of the subfactors on which the relative impact of various levels of subfactor activity can be measured.
6. Determine probabilistic estimates of expected operational performance levels with regard to subfactor utility scales.
7. Perform Monte Carlo simulations of future facility construction and operation under conditions of uncertainty to obtain aggregate performance profiles.

8. Develop overall desirability indices for weighted aggregate totals of monetary and nonmonetary values.
9. Perform alternative site comparisons and determine the sensitivity of each selection due to variability in aggregate measures.

The objective of this work is not the development of an elaborate mathematical model which possesses sophistication far beyond the quality of available data, but rather to present a framework within which it is possible to make decisions which are logical, direct, and amenable to common sense. The simulation procedure utilized permits the employment of various types of sensitivity studies and also allows the analyst the opportunity to evaluate the effect of bias within the data involving subjective judgements.

II. GENERALIZED SITING EVALUATIONS

Electric utilities are traditionally faced with the difficult, but relatively well-defined problem, of planning, constructing, and operating electric power systems. The objectives of providing a reliable source of electrical power at a minimum cost are not too unlike those of many other businesses. The primary differences are, of course, concerned with the monopolistic nature of a utility and the associated regulatory environment in which decisions regarding levels and prices of service are made. One additional planning factor which concerns the engineering analyst is the long lead time required for the design and construction of additional generating capacity. For instance, a 1000 megawatt (electrical) nuclear power plant on a newly proposed site today would probably not be completed for at least eight years, and some planners consider 10 years a more likely estimate (Whitman, 1975). These factors enter into the general site selection process and development of basic cost estimates which follows.

Generalized Site Selection Procedure

The generalized site selection procedure followed by a typical electrical utility is akin to that followed by any major firm searching for a new manufacturing location. The criteria used in evaluating potential sites are not in all cases similar and the importance placed on selected site attributes varies considerably, but the stepwise selection procedure should remain essentially the same. A generalized site selection and evaluation procedure for determining power plant locations is illustrated in Figure 1.

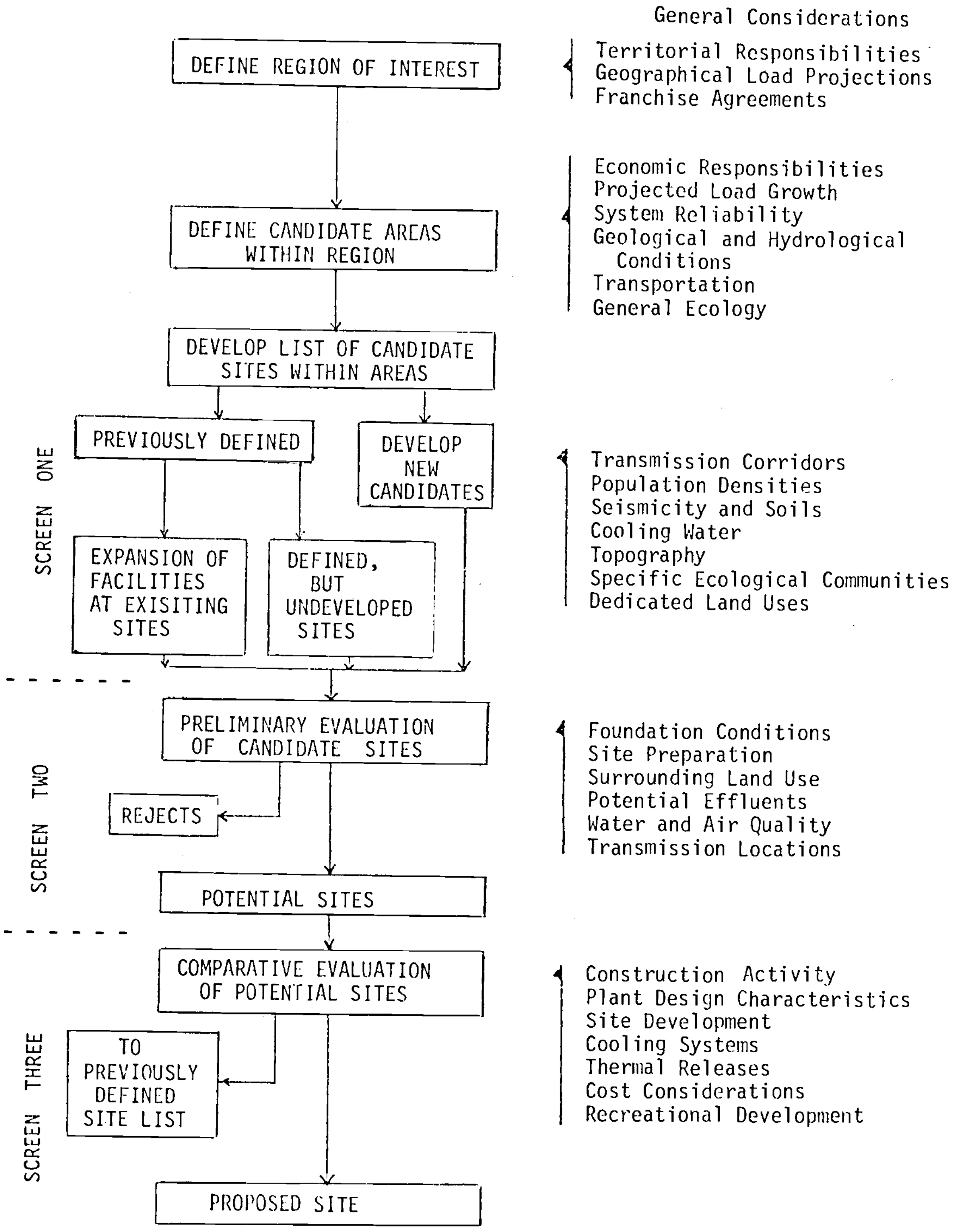


Figure 1. Generalized Site Selection Procedure For Power Plants

The process shown starts with defining the region in which the facility is to be located. As was previously stated, this paper assumes that the decision to increase regional generating capacity has been made. However, several sources of information concerning system expansion studies are available in current literature (Henault, et al., 1970; Rogers, 1970; Booth, 1970; Farrar and Woodruff, 1973; Scheppe, et al., 1974).

Within the region of interest exist one or more candidate areas which are to be investigated for potential sites. These potential sites may be newly established as a result of currently ongoing surveys or may have been previously identified as being potentially suitable for the construction of power producing facilities. The collection of candidate sites is then subjected to the evaluation procedure and subsequent elimination operations until all are rejected as unlicensable, or one is finally selected as the proposed site for which the utility applies for a construction permit.

Determination of Candidate Areas

The identification of candidate areas within a region of interest involves the utilization of broad decision criteria. General considerations involving (1) systems planning, (2) safety, (3) engineering, and (4) environmental effects are usually made and applied on an acceptable - not acceptable basis. These considerations are described below.

(1) System planning factors include responsibilities with regard to franchise agreements and expected customer demand growth, along with the installation of capacity required to maintain an acceptable level of system reliability. Often decisions

also include factors associated with territorial responsibilities and power trade agreements with neighboring utilities.

(2) The influence of safety in the identification of candidate areas is primarily that of assuring that the characteristics of these areas are acceptable to various state and federal licensing agencies. Consideration must be given to various demographic, geographic, and geological characteristics of the region. Evidence of existing earth faultlines, past earthquake activity, and the probability of site area flooding must be considered. Additionally, the avoidance of concentrated high population areas is usually desirable, and with nuclear powered units mandatory.

(3) Candidate area evaluation with regard to engineering factors involves the development of feasibility-cost studies in a broad sense. Basic estimates concerning soil conditions, transportation system capabilities, and the adequacy of reliable water supplies are generally all that is required. Difficulties in all of these areas can usually be overcome at some expense, but the availability of water for cooling is probably the most critical. A minimum acceptance level for measuring all attributes would probably be used as a screening technique on these factors.

(4) Environmental considerations affecting the selection of candidate areas are primarily intended to delineate potential problems. Difficulties regarding preplanned land use in parks, military areas, natural reserves, and the like must be avoided. Additionally, the potential for intrusion into environmentally

sensitive areas such as wetlands, habitats of endangered species, and unique vegetation can develop into conflict with various groups of interested citizens.

Candidate area selection utilizes screening techniques for determining the possible suitability of relatively large geographic area. Little or no comparison between areas is performed at this point because area-wide values are virtually meaningless due to the large variability within areas.

Determination of Candidate Sites

The objective of the candidate site determination stage is to derive a list of specific locations which are judged potentially acceptable for development as a power plant site. Determination of candidate sites begins when attention is shifted to the consideration of specific plant-size locations rather than area-wide considerations. The transition out of this stage occurs when a finite number of clearly developed sites have been identified for inclusion in the comparative elvaluation procedure.

The development of a collection of candidate sites usually involves the application of a number of different analysis techniques. The methods employed depend upon the general characteristics of the region, the number of sites being compared, and the results of evaluations made in previous steps. As the evaluation proceeds, the number of alternatives is generally reduced, and as this reduction takes place, the considerations become more site-specific.

At this level of the analysis, systems planning considerations acquire a somewhat reduced level of importance, with engineering and environmental factors becoming more of a concern. This shift is due primarily to the more general nature of systems planning and its general lack of importance as to where an area of specific site is located as long as the area itself is acceptable. The primary systems level concern is the accessibility of transmission corridors and general proximity to load centers. This consideration is often included as a portion of the engineering evaluation and minimal specific systems planning is performed at this stage.

There is also an increased emphasis on other engineering considerations with site related factors receiving more emphasis than those concerning technical design parameters. However, possible alternative designs must be kept in mind at this point, as engineering modifications can often compensate for otherwise unfavorable factors. Engineering related factors should include:

- Topography and soil conditions
- Adequate access for heavy equipment
- Ample transportation for construction and operational activities
- Availability of an adequate supply of cooling water
- Cooling water intake and outfall design characteristics
- Availability of construction labor and materials
- Transmission and substation layouts
- General plant layout characteristics

Additional engineering factors which should be considered in the construction of both fossil fueled and nuclear generating stations can be found in Anderson, et al., (1975).

Environmental considerations at this stage include a broad range of factors relating both to the natural environment and to human activities in the immediate site vacinity. A prime concern at this point is the identification of all potentially significant factors in this area. Early impact assessments are usually of a more generalized nature and become more detailed as the number of potential sites is reduced. The process of natural attrition by the employment of gradually increasing investigative detail is a useful screening step in the evaluation procedure.

A generalized listing of environmental factors which should be considered would include:

- Water quality
- Air quality
- Land use compatibility
- Hydrology
- Meteorology and climatology
- Aesthetics
- Specific ecological communities
- Wet lands and estuaries
- Historical and archeological sites
- Transmission systems
- Recreational facilities
- Socio-economic factors

Additional information concerning individual state legislation in this area is available from Best (1972), and complete data concerning the preparation of environmental reports for nuclear power stations are available in United State Nuclear Regulatory Commission 4.2 (1975).

Various evaluative and comparative techniques for studying multi-attributed alternatives are used in this stage of the site selection process. Some of these involve the direct generation of cost data such as are shown in the following section, while others use comparative procedures for qualitative type data. Some of these techniques are further developed in Chapter III.

Development of Direct Cost Estimates

The primary emphasis of this paper is the development of a procedure for the integration of qualitative impact variables into the site-design evaluation process, but the inclusion of valid direct cost estimates is an integral part of determining overall alternative desirability. It is, therefore, necessary to at least briefly investigate the procedure through which these data are obtained and the desirability of using probabilistic estimates.

Early in the candidate area selection process, tentative decisions must be made as to the general configuration of the facility. Systems planning acitivities include estimates of the total generating capacity required, possible fuel options, and the size and number of units required to meet the stated capability. As the number of sites being considered decreases, increasingly detailed descriptive data for the remaining sites are developed. These developments permit more precise engineering cost estimates for the remaining site-design alternatives. Some sites may have several different engineering configurations proposed for a single location. The use of oil, gas, coal, or nuclear fuels may be considered along with various combinations of boiler and generator systems. Cooling system alternatives could include once-through flow from natural water sources, natural or forced-draft cooling towers, and cooling ponds with or without spray equipment. The investigation of all these alternatives is part of the engineering design process.

As the tentative site-design combinations become fewer in number and more detailed in concept, more exact engineering cost estimates are developed. These estimates, like those on any large project, are quantitative, but are based in part on the subjective judgement. Similarities in design between the proposed facility and those already in operation generally contribute to greater estimating accuracy. However, no two facilities are identical, and variation is always present in construction and operation cost estimates.

Variations in estimates, which cause uncertainty in cost projection are particularly noticeable today. Large capital cost increases have characterized the period since 1965. Estimated costs for Light Water Reactor (LWR) power plants have increased from about $134/KW(e) in 1967 to over $720/KW(e) in 1974. During this same period, estimated costs for all coal-fired generation facilities have increased from $105/KW(e) to $600/KW(e) - (Whitman, 1975). The costs involved in constructing gas and oil fueled units have increased correspondingly, but the rapidly escalating costs of these fuels have raised annual operating expenses to the point where they are seldom being considered in capacity expansion studies. It is difficult to anticipate how much costs will increase in the near future, and almost impossible to predict for the distant future.

Most attempts to predict future costs are characterized by the use of single point or "most likely" estimates. Such an approach fails to account for the technological uncertainty associated with component parameter values. Of late, some effort has been forthcoming to analyze the sensitivity of power system economics to various operating (Henderson and Bauhs, 1974; Klepper, 1975), technological (Rathbun, 1975) and financial (Gulbrand and Leung, 1974) factors.

The underlying interdependent causative factors for the increased variability in power plant cost estimates include:

1. The trend away from turnkey contracts
2. Increased project scope and complexity resulting in additional material, labor, equipment, and engineering design content
3. Lengthened project schedules associated with the increased scope and complexity
4. Escalations in interest rates, labor costs, and material expenses during extended project schedules
5. Mid-project changes of regulatory guidelines and imposition of additional equipment standards
6. Increased management content due to project size, complexity, and regulatory requirements
7. Prolonged litigation of legal actions concerning environmental and social effects of construction and operation

The estimated direct costs used in the research came in part from studies conducted by Sullivan (1974) and by West and Sullivan (1975) as a portion of the work funded by National Science Foundation Grant GI-38222. The data provided are estimates developed for the construction of a two-unit nuclear power station located in the southeastern United States. The candidate site impact factors presented in Chapter V were later collected in this same area, thus permitting the integration of these data bases into a composite evaluation procedure.

Direct costs associated with electric power production were calculated through the use of PACTOLUS, a computer code developed by Bloomster, Nail, and Haffner (1970) at Battelle Northwest Laboratories. This program considers inputs from throughout the uranium fuel cycle and requires data on mass and energy balances, processing times, operating expenses, capital costs, and various financial factors. A modification of the code permits the simulation of total power costs through the input of data in the form of probability density function rather than point estimates.

The following procedure was used to develop a distribution of expected direct costs:

1. Establish an expected unit cost by running the program with most likely single point estimates for each input variable.
2. Determine the most significant input data by increasing the most likely value of each parameter by 20% while holding all other values constant. The result of individual trials are compared to the previously obtained average value.
3. Develop probability distributions describing the expected variance of the most significant values.
4. Employ density functions of the most significant parameters to develop aggregate cost profiles through the use of simulation.

A list of input parameters required for the PACTOLUS program is shown in Table I. These data are based on information collected in 1974 and were the best estimates of values for a particular 1125 MW(e) generating unit. Using these data, a baseline power cost of 11.9846 mills/KWh was obtained and was used for comparative purposes in the

TABLE I. INPUT PARAMETERS TO THE PACTOLUS
Code for example Nuclear Plant on a Per Unit Basis

		1974 Data
1)	Bond Repayment Option	Uniform Annual Payment
2)	Depreciation	Straight Line
3)	Inventory Accounting	FIFO
4)	First Core Interest Rate	8%
5)	Core Fabrication Losses	.45%
6)	Total Capital Costs	$\$3.23 \times 10^8$
7)	Thermal-to-Electrical Conversion Efficiency	32.9%
8)	Plant Base Operating Cost	$\$4.02 \times 10^6$/yr.
9)	Variable Plant Operating Cost	$\$3.377 \times 10^6$/yr.
10)	Interim Capital Replacements Fraction of Plant Investment	.0035
11)	Nuclear Liability Insurance	$334,500/yr.
12)	Property Insurance Fraction of Plant Investment/year	.0025
13)	Total Taxes	$2,850,000
14)	Property tax on plant and initial care, fraction/year	.027
15)	Reactor Startup Date, Year	1976
16)	Depreciable Life, Years	35
17)	Construction Time, Years	8
18)	Fabrication Time, Days	180
19)	Pre-Reactor Inventory Time, Days	90
20)	Post-Reactor Cooling Time, Days	150
21)	Reactor Operating Lifetime, Years	35
22)	Separative duty, $/kg	33.28
23)	UF6 Conversion Charge, $/kg	2.58
24)	U-233 Price, $/gram	14
25)	PU-239 Price, $/gram	8
26)	PU-241 Price, $/gram	8
27)	TH-232 Price, $/gram	.0102
28)	*Core Fabrication Costs, $/kg	95 112.53
29)	*Core Reprocessing Cost, $/kg	30 36.9
30)	*Additional Fabrication Cost When Handling Recycle Fuels, $/kg	15 17.83
31)	*Uranium Feed Price, $/lb. U-308	7.5 50

* Data input to PACTOLUS requires that a bounded interval of the cost projection for these parameters be determined. The first-listed price projection pertains to the startup date for the plant (1976). The second price projection is valid at the end of plant life (2015).

sensitivity study. Results of that analysis showed the following parameters were the most significant in their effect on overall power cost:

Initial investment
Separative Duty
Core Fabrication Cost
Uranium Feed Price

Probability distributions of expected future variations in these parameters were developed using subjectively derived information. This information was obtained through the use of a series of questionnaires presented to engineering personnel involved in the facility design project. The modified computer code was then used to simulate the distribution of electrical power costs resulting from the variability of the most significant factors. Results of this simulation are shown in Table II.

The results of this data collection and simulation will be integrated into the total site-design evaluation process in Chapter VI. Before it is possible to obtain a composite value for a particular alternative, it will be necessary to develop a method for the inclusion of nonmonetary data. This problem will be investigated further in the following chapter.

TABLE II. PACTOLUS SIMULATION RESULTS FOR EXAMPLE NUCLEAR PLANT

Interval (Mills/KWh)	Percent of Total*	Cumulative Percent
10.00 - 11.00	0.0	0.0
11.00 - 12.00	0.8	0.8
12.00 - 13.00	8.6	9.4
13.00 - 14.00	16.0	25.4
14.00 - 15.00	18.0	43.4
15.00 - 16.00	16.8	66.2
16.00 - 17.00	18.6	78.8
17.00 - 18.00	9.0	87.8
18.00 - 19.00	8.8	96.6
19.00 - 20.00	2.6	99.2
20.00 - 21.00	0.6	99.8
21.00 - 22.00	0.2	100.0
22.00 - 23.00	0.0	100.0

* Results of 500 simulation cycles

III. CLASSICAL DECISION MAKING METHODS

The evaluation and subsequent selection of the best alternative from among an array of closely similar multiattributed candidates is usually a difficult task. Methods have been developed to assist the analyst concerned with multiple-attributed decision making. Some of these techniques are applicable to measuring the environmental impact of site-design proposals.

Every action that is taken during the construction and operation of a power station has some effect on the surrounding environment; the term "environment" being applied in a broad sense to include all forms of societal and biological systems. Analysis of such effects requires the identification of the factor causing the effect, the system or systems affected, magnitude of each effect, and the relative importance of these magnitudes on the environment. The measure of importance may concern only a single identifiable environmental parameter, but often must include the consequences of single system alteration on other systems which are present.

Each of the site-design alternatives can be described by a list of attributes or characteristics. Many are simply physical descriptions of the design and others are factors involving cost. The present focus is on those attributes which describe the nonmonetary effects of construction and operation. The development of a list of relevant factors can be as simple or as extensive as the analyst wishes, but often this activity is physically limited by the time and resources available. In an extreme case, a single aggregate attribute such as "expected environmental impact per kilowatt hour (KWh) of power produced" might be employed. However, in a situation where many factors comprise the aggregate attribute, it is obviously necessary to develop a method of isolating and identifying these components.

In the situation being considered, the use of a questionnaire is often the most effective means of obtaining a list of relevant factors. Persons knowledgeable in the areas of possible significant impact and familiar with the engineering, environmental, and other technical specialties should be asked to contribute ideas. Elaboration of this technique and other areas concerned with data collection activities will be discussed in Chapter V.

Elementary Scaling Methods

After identifying attributes to be included in the analysis, it is necessary to obtain reliable estimates of their values for each of the alternatives under consideration. At this point, the assumption is made that each of the alternatives can be described in terms of the attributes it possesses or the impact it will have in each of the attribute categories. While this may seem an indirect way to describe an alternative, it is an essential step in developing the collection of values into a classical decision model. For illustrative purposes, a highly simplified example is shown in Table III. Note that in this simple case, the attributes are described in both qualitative and quantitative terms. Direct or monetary costs are not included in order to reduce the complexity of the example at this point. However, their inclusion in the basic decision model format is simple and straightforward (Fasal, 1965; Brown and Gibson, 1971).

TABLE III. EXAMPLE PROBLEM ILLUSTRATING MULTIATTRIBUTED ALTERNATIVES

ATTRIBUTE	ALTERNATIVE			
	I	II	III	IV
(1) Land Requirements (Acres)	6400	6000	1600	2000
(2) Consumptive Water Use (Acre-Ft/Yr)	70000	70000	25000	30000
(3) Impact on area aquatic life	B	B	C	C
(4) Impact on adjoining land use	E	D	B	C
(5) Impact on surrounding air quality	B	B	C	D
(6) Aesthetic impact	A	B	D	E

Where A represents negligible unfavorable impact

B represents low unfavorable impact

C represents medium unfavorable impact

D represents high unfavorable impact

E represents very high unfavorable impact

Development of such a tabular display presents no problems after the relevant data have been collected. Comparisons of data in this form have been used with varying degrees of success as the primary phase of analyses which depend heavily upon subjective judgement (Leopold, 1971). However, the mental digestion of an array which contains both quantitative and qualitative values and which often displays numerical data containing variations in orders of magnitude between attributes is difficult. In order to somewhat alleviate this difficulty, a common approach is to first develop a comparable numerical scale for all attribute values.

A first step in this process would be the development of a technique which will allow the approximate quantification of the qualitative attribute values. Given information of this type, the most common quantification method is to develop a cardinal scaling procedure where the various applicable qualitative terms are associated with numbers on a numeric scale. The choice of a ten-point or one hundred-point scale is usually logical, since most people seemingly have an intuitive feel for such ranges. In this example, a ten-point scaling will be used. In such a situation, the most obviously identifiable values are the end points. The 0 point will thus represent the minimum attribute value that is physically or practically attainable, while the maximum attribute value that is physically or practically attainable will correspond to the 10 point of the scale.

The question of whether high values on the scale represent highly favorable or highly unfavorable characteristics must be kept in mind. In the simplified example being used, all high impact values are deemed undesirable, but an attribute representing a desirable characteristic such as "Recreational Potential" with a high impact would also be related to a high value. In order to eliminate this difficulty, the scale can simply be reversed such that the 0 point represents a very high attainment of a positive attribute. Scales using "plus" and "minus" values over the -10 to +10 scale are also employed (Cleary, et al., 1975).

It is obvious that a certain amount of arbitrariness exists in such a method. Many other scales are possible and sometimes attempts are made to check the consistency of the results obtained (Fishburn, 1965). However, for the purposes of this example, the 0 to 10 assignment method will be adequate.

It should also be pointed out, that the values illustrated imply several critical relationships. Most importantly, it is assumed that a scale value of 8.0 is twice as favorable as 4.0, thus a "high" value is over twice as favorable as a "low" value and seven times more favorable than a "very low" value. Additionally, the use of the values across attributes implies that the difference between "high" and "low" impact on Land Utilization is identical to the difference between "high" and "low" impact on Area Water Quality. This latter characteristic is especially critical when importance weightings are later assigned to the various attributes.

Application of the scaling technique thus permits quantification of the original qualitative factors, but the numerical values for Land Required and Consumptive Use of Water are not yet on comparable scales. Since smaller values are preferable in terms of overall impact, scaling must be performed so as to accurately conform to this relationship. An initial thought may be that the most straightforward method is to set the minimum value (in this case 1600 acres for land requirements) equal to the scaling equivalent of "very low" and proceed from there as in the qualifiable factors case. This procedure would result in alternative III having an attribute value of $\frac{6400}{1600}$ x 1.0 (very low) = 4.00 which seems reasonable. However, if one of the alternatives required over 16,000 acres of land, the equivalent scale value would be greater than 10.0 and thus would violate the original guidelines. At this point, it must be remembered that the upper and lower values of the scaled variables are to be those which are considered practically or physically reasonable. It may be that a range of land usage from 1,000 to 10,000 acres is considered the feasible range for such a project. In this case, the value of 1,000 could be scaled as "very low" and values for the various alternatives could be scaled accordingly. If the ends of the feasible range are not well defined, it will probably suffice to treat the maximum value available as the largest which will occur. In this case, the raw attribute value of 6400 would be assigned a scale value of 10.0, and the other raw values would be scaled accordingly. The complete array of scaled attribute values is shown in Table IV.

TABLE IV. EXAMPLE PROBLEM FOLLOWING CONVERSION OF ALL FACTORS TO COMPARABLE VALUES

ATTRIBUTE	ALTERNATIVE			
	I	II	III	IV
(1) Land Requirements	10.0	9.4	2.5	3.2
(2) Water use	10.0	10.0	3.5	4.3
(3) Impact on water	3.0	3.0	5.0	5.0
(4) Impact on land use	9.0	7.0	3.0	5.0
(5) Impact on air	3.0	3.0	5.0	7.0
(6) Aesthetic	1.0	3.0	7.0	9.0

CONVERSION SCALE

QUALITATIVE IMPACT	QUANTITATIVE VALUE
Very High	10.0
	9.0
	8.0
High	7.0
	6.0
Average	5.0
	4.0
Low	3.0
	2.0
Very Low	1.0
	0.0

Decision Making Among Multiple-Attributed Alternatives

The decision maker faced with a problem involving multiple-attributed alternatives may use one of several evaluative techniques during the analysis procedure. At this point, it may prove useful to discuss some of the more general methods which are available, along with the basic assumptions and information requirements of each. While some of the approaches mentioned are simply descriptive models of basic decision making logic, the normative implications may prove of interest.

In the previously developed illustrative problem, each alternative was defined by a particular collection of attribute values. The number of attributes, n, used in this definition is said to determine the dimensionality of the basic decision problem. Analysis methods are generally classified into two primary groups. Methods which simultaneously involve the consideration of all available descriptive attributes are said to be fully dimensional. At the other extreme, are techniques which reduce the n-attribute problem to one of a single dimension. The operation of these single dimensional methods is usually based on some technique which removes n-1 dimensions from consideration or by imposing assumptions that allow the n dimensions to be combined into a one-dimensional space.

It would be desirable to consider all problems in their fully dimensional state. However, both the time and effort required for such complex analyses are usually prohibitive, and it is often possible to reduce the dimensionality of the original problem without a significant loss of information or accuracy. Fully dimensional methods are also sometimes useful in reducing the collection of available alternatives to a more manageable number before utilizing available reduced dimensionality methods as the final selection technique.

Intermediate between the full dimension and single dimension methods are some which may consider two or more attributes at a time or at least allow the dimensionality to be greater than one but less than n. These methods along with those requiring a combination of the above techniques are presented below.

Symbolic Representation

Before continuing the discussion of representative analysis techniques, it will be useful to more fully develop the symbolic notation describing the example problem. Referring to Table V, the decision maker is portrayed as attempting to choose between a set of alternatives $A = (A_1, A_2, A_3, \ldots A_m)$ which are described by a set of attributes or factors $F = (F_1, F_2, F_3, \ldots F_n)$. The various individual attributes making up an alternative can thus be described as an element of the Cartesian product $(F_1 \times F_2 \times \ldots \times F_m)$ the generic form of a particular alternative $(f_1, f_2, \ldots, f_m)_j$ will be denoted as A_j. The i th attribute of the j^{th} alternative will be denoted as f_{ij}. For simplicity, it can be assumed that this notation will represent the scaled values rather than raw data, and thus all are on comparable, numerical (cardinal) scales.

One additional term will be added to the symbolic representation at this point. A factor importance value or weight, W_i, is included to permit an expanded discussion of attribute importance weighting in Chapter V.

TABLE V. SYMBOLIC REPRESENTATION OF MULTIATTRIBUTES DECISION MATRIX

ATTRIBUTES	IMPORTANCE WEIGHT	ALTERNATIVES			
F_i	w_i	A_1	A_2	----	A_m
F_1	w_1	f_{11}	f_{12}	-	f_{im}
F_2	w_2	f_{21}	f_{22}	-	f_{2m}
⋮	.	.	.	.	.
F_n	w_n	f_{n1}	f_{n2}	.	f_{nm}

Fully Dimensional Techniques

The evaluative treatment of each dimension or attribute in an independent and separate comparative step is referred to as a fully dimensional method. The two primary methods which employ this technique in multiattributed decision making are dominance and satisficing. In both methods, each attribute must meet certain requirements, and is forced to stand alone during the analysis. That is, tradeoffs and balances are not permitted and the weaker attributes of an alternative cannot be offset by any stronger attributes which may be present.

Dominance

In applying the dominance procedure, the analyst makes decisions based solely upon whether or not a particular attribute value is more preferred than another. Thus in the comparison of two alternatives, if one of those compared has more preferred values for each and every attribute, then it can be said that this alternative dominates the other. In the siting example being considered, lower values are preferred over higher, but in a maximization situation, the higher values would be preferable. This procedure can be broadened somewhat if all available alternatives are being compared in a single operation, to say that if one alternative has preferred values for each attribute when compared to all other alternatives, then it dominates the entire set and is thus an optimum choice. A slightly weakened version of the concept would be the case in which an alternative is at least as good as the others on all attributes and is actually superior on at least one of them. In this situation, that alternative could still be considered dominative. Conversely, if one alternative is worse than at least one other alternative for one or more attributes and is no better than equivalent for the remaining factors, it can be said that the former alternative is dominated by the latter. As an illustration, this situation exists in the example problem as alternative III is equivalent to alternative IV in attributes 3 and 4 and is superior in attributes 1, 2, 5, and 6, thus III is said to dominate IV. At this point, alternative IV could be dropped from further consideration which would effectively reduce the analysis required if any further comparisons were to be developed. However, since this is simply an illustrative exercise, all alternatives will still be considered viable in following discussions.

Dominance procedures can be used on both quantitative and qualitative or scaled data. That is, comparisons between "high" and "low" can be made as easily as between numerical data. The analyst needs make no assumptions about the degree of preference for particular attribute values and thus is not required to be concerned with the difference between "high" and "low" as compared to the difference between "high" and "very low".

As one of the most easily applied and understood of common comparison techniques, dominance has been employed both intuitively and as a formal procedure for many years. One of the first formal proponents of its use in economics was Pareto (1848-1923), and thus non-dominated alternatives are sometimes referred to as being Pareto-optimal (MacCrimmon, 1968).

In notational form, dominance could be described as follows: If one alternative is denoted by $(f_1, f_2, \ldots f_n)_a$ and the second by $(f_1, f_2, \ldots f_n)_b$, then the first alternative dominates the second if $f_{i'a} \geq f_{i'b}$ for all i and further $f_{i'a} > f_{i'b}$ for some i'.

Referring to the overall site evaluation procedure shown in Figure 1, comparisons involving dominance would most likely be employed at screening Steps 1 and 2.

Satisficing

The application of the satisficing procedure requires that the analyst must supply either minimum or maximum acceptable attribute levels. In this particular example, minimal environmental impact is desired and thus upper limits or specifications may be set. Naturally, in a maximization problem, minimum acceptable limits of performance could be implemented. The values thus set may vary from attribute to attribute and a "tight" limit on one factor has no effect on the others as they are treated independently.

In the example problem, limits could be imposed on either the quantitative or qualitative variables before scaling. The various attribute values of the alternatives would be compared to these standards, one at a time and either accepted or rejected. Those alternatives which passed the first satisficing step would then be tested in the second comparison. For example, if an upper unit of 6000 acres was placed on available land, then alternative I would fail to meet the standard and would be dropped as unacceptable. A second criterion may be that impact on air quality be held to a minimal or "low" level. A comparison of the remaining alternatives to this standard would then eliminate alternatives III and IV. In this particular situation, an optimum acceptable alternative, II, has been obtained directly whereas the possibility of this occurring in actual practice is limited.

The satisficing method, in contrast to the dominance method, allows successive changes in the acceptability requirements and thus can be "tightened-up" to reduce the feasible set of alternatives. This procedure is very useful in cases where a large number of multiattributed alternatives are included in the initial feasible set. Care should be taken at this point not to set a single attribute value excessively tight in order to simplify the selection process. It should also be noted that the utilization of maximum or minimum standard values as an acceptable or rejection criteria for each of the attributes does not allow an alternative any credit for having an especially strong value in any other attribute. In this way, satisficing and dominance are somewhat similar in their limitations. However, since the satisficing procedure allows the decision maker to make several successive elimination trials with varying sets of criteria, this technique may be considered a more powerful decision tool than dominance (Simon, 1955).

In notational form, satisficing can be described as follows: Given that a set of maximum attribute values $(g_1, g_2, \ldots g_n)$ is defined on F_1, F_2, F_3. An alternative A_j is satisfactory only if $g_i > f_{ij}$ for all i. Unsatisfactory alternatives are those for which $f_{ij} > g$ for some value i.

Satisficing is particularly useful in eliminating unsatisfactory alternatives in cases where specific limitations are placed on attributes by circumstances beyond the control of the decision maker. Regulatory limits may be imposed on various phases of the construction and operation of power plants. Satisficing methods utilizing variable limits could be employed at all three screening levels shown in Figure 1 .

Single Dimension Methods

The following procedures all have the characteristic of reducing the n attribute comparison problem to one consisting of a single dimension. Each alternative is thus represented by only one value in the final step of the comparison process. The first three methods are simply adaptations of principles used for alternative selection when complete uncertainty as to operational conditions exists. A minimum amount of information is required for implementation of these techniques, but there must be a high degree of comparability among the attribute measuring scales. The last method investigated utilizes attribute importance weightings in an effort to map the comparative data from the n dimensional state to a single numerical scale.

Minimax

In applying the minimax criterion, the decision maker is saying in effect that he wishes to minimize the possible maximum of all impacts that could possibly occur. The comparison process is performed by first examining the attribute values of each alternative, noting the highest value for each, and then selecting the alternative with the lowest noted value. This process results in the selection of the alternative displaying the minimum of all the maximum attribute values or minimax. In a situation where a maximization of impact, output, or profit is the desired goal, the procedure is reversed and is thus called maximin.

Since in many instances, the lowest values come from differing attributes among the various alternatives, the final choice is made on single nonsimilar values which must be highly comparable. In order to obtain this degree of comparability, care must be taken in evaluating the alternatives being inspected, and their attributes must be measured on a common scale. Often some type of transformation must be applied to portions of the original data in order to develop the comparison.

In applying this technique to the example problem, it is noted that the highest impact values for the various attributes are as follows: Alternative I = 10.0, II = 10.0, III = 7.0, and IV = 9.0. Since the smallest of these values is 7.0, alternative III would be selected as having the minimum of the maximum values. If a tie should result at this point, it may be broken by using the same comparison technique among the remaining attributes of those alternatives which are tied.

The minimax (or maximin) obviously makes use of only a small part of the information available. In fact, the more information that is available, the higher the proportion of waste. If information concerning a large number of attributes is available, the process selects an alternative which is average in all respects rather than a strong overall alternative with a single weak point.

The strongest argument that can be made for the use of this technique is that it offers a possible consistency over a time span in which numerous choices must be made, and that it directs attention to the worst outcomes and then points out the alternative that avoids the worst. In a general decision making situation, only the most pessimistic analyst would consistently use this procedure as his sole decision criterion. The technique is widely discussed and forms one of the bases for game theory strategies where competition against a knowing and logical opponent is involved (von Neumann and Morgenstern, 1953).

Minimin

The reverse philosophical approach to the pessimistic analysis presented in minimax is the optimistically oriented minimin procedure. In applying this procedure, an alternative is represented by the most favorable attribute value, rather than the worst, and then the alternative displaying the best of the best is selected. In minimization problems, such as the one being pursued, minimum impact values are the most preferred, thus the minimum of these minimums would be selected, hence the name minimin. In situations where maximization is the goal, the alternative displaying the maximum of the maximum attribute value would be selected, thus the maximax procedure results. In the comparative example, alternative I has a minimum value of 1.0, II of 3.0, III of 3.0, and IV of 3.2. Alternative I is thus selected by reason of having the minimum of minimum impacts.

It should be emphasized that in actual multiattributed decision making, the probability of this procedure and the previously discussed minimax selecting the same alternative is generally quite small.

This technique tends to select an alternative displaying a single very low or very high if maximizing, attribute value with no concern as to what values the other n-1 attributes may have. It should be noted that in the above example, alternative I has two extremely high impacts in attributes 1 and 2, but it is still selected by the minimin procedure. Naturally, the comments concerning attribute scaling and comparability in the minimax procedure apply equally as well in this case.

Lexicography

The strict definition of a lexicon refers to "a book containing an alphabet arrangement of words..." (Webster, 1956), thus a dictionary. Lexicography in a slightly broader sense is the act of arranging in order some collection of similar things or items. In the case of multiattributed decision making, it refers to the ordering of attributes by degree of importance, and then comparing alternatives based upon this importance ranking. Since alternatives are compared using only one attribute (or dimension) at a time for evaluative purposes, this procedure can still be defined as single-dimensional in nature.

The lexicographic procedure consists of basically two steps. First, the various attributes are ranked in order of importance by those involved in the decision making process. Secondly, the comparison of all the alternatives is performed based on the highest ranking attribute. If one alternative is predominate over all others, then it is chosen and the process ends. On the other hand, if no single winner is produced, all the alternatives with less than the common maximal value are dropped from further consideration and a comparison is then made over those remaining alternatives using the second ranked attribute. This process of elimination continues until either a single alternative is selected or all attributes have been considered. In comparison with the minimax and minimin procedures, the lexicographic method is of a somewhat higher level in that it requires that ranking information be provided. The strict requirement of comparability between attribute values is also eliminated since the attributes are compared singularly and thus do not need to be evaluated on equal scales. However, the lexicography procedure exhibits an incompleteness comparable to the other techniques in that since attributes are compared singularly, an alternative with one exceptionally low (or high) value could be selected on the first cycle without regard to its other characteristics.

In the power plant example, it can be seen that the selection of Consumptive Water Use as the top ranked attribute would result in alternative III being chosen while the selection of Aesthetics as the attribute given the highest ranking would result in the selection of alternative I. However, alternatives such as number II with all average or near average attribute values would rarely, if ever, be selected.

An extension of the basic lexicographic process is to develop a comparison of alternatives where each of the attributes are considered in turn to have the number one ranking. As the comparison progresses, the number of times each alternative is either singularly dominative or tied for the dominative position is tabulated. The alternative emerging with the largest tabulated number of "wins" is thus selected. Ties can be broken by checking second place rankings and so on down the line. However, this process starts to approach the additive weighting technique discussed in the following section.

Extensions of lexicography are widely employed, primarily as a result of its limited need for numerical information. Examples of its use may be found in the fields of plant location studies, plant layout, and as an alternative to a numerical scale utility theory applications (Hausner, 1954; Chipman, 1960).

Additive Weighting

The lexicographic technique allows the decision maker an opportunity to use a perceived order of attribute importance in the evaluation process. However, the employment of a rank based selection procedure can easily overlook an alternative which is above average in all respects, but not superior in any. In cases such as this, and under conditions where no single attribute is overwhelmingly critical, it is often useful to employ a technique based on the relative importance of each attribute. Importance judgements are contingent upon a large number of factors, but it is assumed that those interested in the selection process will have such factors in mind.

If it is possible to develop a numerical value of importance, then each attribute may be weighted by this measure in order to obtain the contribution of the attribute to each alternative. The total alternative weighted value can then be obtained through the summing of its component weighted attribute values. All attribute values are included in this technique, but since the final decision is made on the basis of a single weighted value for each alternative, the method is classified as single dimensional.

The notational equation describing the weighted value of an alternative (J) is:

$$A_j^* = \sum_{i=1}^{n} W_i \cdot f_{ij}$$

where A* represents the comparative value of the alternative. Since the methods employed in obtaining this value consist of the regular arithmetical operations of multiplication and addition, the attribute values must be both numerical and comparable. Further, it is also very important to develop a reasonable basis on which to form the weights reflecting the importance of each attribute.

For the purposes of developing an illustrative example, it can be assumed that the following weights have been determined for each of the attributes presented in the earlier problem: Land Required 0.10, Water Consumed 0.25, Impact on Water 0.20, Impact on Land 0.15, Impact on Air 0.20, Aesthetics 0.10. In this case, the weights have been normalized to sum to 1.0, but this is not absolutely essential. This step does, however, permit a rapid comparison of the relative importance of each attribute, and also allows for comparison between studies of similar type problems. Multiplying these weights by the corresponding attribute values for alternative I results in the following calculation:

$$A_1^* = (10.0 \times 0.10) + (10.0 \times 0.25) + (3.0 \times 0.20) + (9.0 \times 0.15)$$
$$+ (3.0 \times 0.20) + (1.0 \times 0.10) = 6.15$$

Performing similar calculations for the remaining alternatives gives the following results:

$A_{I}^{*} = 6.15$, $A_{II}^{*} = 5.99$, $A_{III}^{*} = 4.28$, $A_{IV}^{*} = 5.46$.

Examination of these results indicate that alternative III would have the least impact under the weighting system employed.

The successful use of this technique depends heavily upon the procedure employed for the selection of attributes and the relative accuracy of the weighting system. The attributes used for descriptive purposes must be as nearly independent as possible, as interdependencies, overlaps, and complementaries between the various factors can give erroneous results upon application of the arithmetical weighting procedure. Further, the procedure is usually quite sensitive to large variations in the importance weightings. It should be noted that 10.0 multiplied by 0.10 and 4.0 multiplied by 0.25 both yield the same product. This operation provides the implication that extrememly large land requirements offset below average water consumption. Such comparisons should be considered for their validity before applying the technique. Additional considerations involving the development of adequate weighting scales will be covered in Chapter V.

Additive weighting techniques can be very powerful tools in multiple-attributed decision making activities. Their widespread use has been shown in studies involving business decision making (Churchman, Ackoff, and Arnoff, 1957), selection of manufacturing designs (Fasal, 1965), development of plant layouts (Apple, 1963), and the estimation of environmental impact (Leopold, et al., 1971). However, the successful employment of this procedure requires that care must be exercised in its use. The validity of the results obtained is dependent upon the development of realistically independent attributes, the determination of comparable attribute values, and the assignment of reasonable importance weightings.

CONCLUSIONS

Classical decision making methods employed for the selection of multiple-attributed alternatives vary widely in scope. The major classifications of such techniques are dependent upon the number of dimensions or attributes which are included in the decision step. Dominance and satisficing procedures are considered full dimensional methods, while minimax, minimin, and lexicographic techniques are defined as single dimensional. Additive weighting is also referred to as a single dimensional method for even though all attributes are included in the analysis, the final selection is based upon a single dimensional array of weighted values.

All of these techniques are relatively easy to understand and use while requiring a minimal amount of input data. Unfortunately, none of them guarantee an optimum answer nor do they allow the inclusion of probabilistic information. However, all may prove of some use to the decision maker. With the dominance and satisficing procedures proving particularly useful early in the analysis, and the additive weighting technique serving as a basis for the development of more comprehensive analysis methods.

IV. PROBABILISTIC DECISION MAKING METHODS

Additive weighting procedures utilizing single point or most likely estimates of attribute values provde a very powerful technique for the evaluation of multiple-attributed problems. However, their application as a decision making tool is somewhat limited due to the fact that most input estimates often contain significant variability. It is, therefore, advisable to extend the development of these models to facilitate the inclusion of probabilistic analysis methods.

Probabilistic Additive Weighting

Probabilistic estimates concerning physical operating parameters can be expressed in two basic forms. The estimates could take the form of a finite number of possible outcomes, each being associated with a discrete probability that the outcome will occur. Or the estimate could be stated as a continuous probability density function over the entire range of possible outcomes. At this point, a method will be developed for the incorporation of discrete probability estimates into the additive weighting procedure.

The number of discrete probability estimates required to accurately describe the variability of input data depends upon the process being modeled and the degree of detail desired by the decision maker. For the purposes of illustrating this procedure, the use of three estimates for each alternative-attribute combination will be sufficient. The practice of obtaining three estimates for the low, high, and most likely values of a parameter is relatively widespread. This procedure can be employed simply to obtain the three most commonly used descriptive values of a process, or as the basis for developing a specific function such as the beta distribution (Greer, 1970).

A useful standard to employ in obtaining these estimates is to consider the low value as that point below which the attribute level will fall only 10 percent of the time. The most likely value is that point which the attribute level is expected to seek, and is not necessarily the midpoint between the high and low values.

The procedure being developed does not, however, force the estimates to be made in this manner. For simplicity it will be assumed that three values will be the maximum used in each case, but they do not have to follow the low, high, most likely method of assignment.

An example of this procedure can be developed through the use of data from the problem employed in Chapter III. Looking at the consumptive water use for alternative III, three estimates could be obtained as follows:

	Low	Most Likely	High
Consumptive Water Use (Acre-ft/year)	21,000	24,500	35,000
Probability	0.20	0.70	0.10
Scaled Value	3.0	3.5	5.0

The expected or mean scaled value can then be calculated.

$$\text{Expected Value} = (3.0 \times 0.2) + (3.5 \times 0.7) + (5.0 \times 0.1) = 3.55$$

The variance of this scaled value is then calculated as

$$\begin{aligned}\text{Variance} &= [(3.02)^2\ (.2) + (3.5 \times 0.7) + (5.0)^2(0.1)] - (3.55)^2 \\ &= 12.875 - 12.603 \\ &= 0.272\end{aligned}$$

Once estimates of this type are obtained for each of the attributes, it is possible to determine the mean and variance of expected impact for the laternative being considered. Results of a series of calculations involving a set of hypothetical data for alternative III are shown in Table VI. For simplicity, the probability estimates have been applied directly to scaled attribute values.

The expected weighted value is simply the sum of the individual products obtained by multiplying each expected attribute value by its importance weight. The variance of this weighted value is obtained as follows:

$$\text{Impact Variance} = \sum_{k=1}^{\text{No. of Attributes}} [\text{Attribute Variance}_k \times (\text{Attribute Weight}_k)^2] .$$

TABLE VI. DETERMINATION OF ALTERNATIVE IMPACT VALUE USING PROBABILISTIC ESTIMATES

(Alternative III only)

Attribute	Estimated Values Scaled	Estimated Probabilities	Mean	Variance	Attribute Weight
(1)	2.5	1.00	2.5	0	0.10
(2)	3.0 3.5 5.0	0.20 0.70 0.10	3.55	0.272	0.25
(3)	4.0 5.0 6.0	0.10 0.80 0.10	5.0	0.200	0.20
(4)	2.5 3.0 3.5	0.20 0.70 0.10	2.95	0.073	0.15
(5)	3.0 5.0 7.0	0.20 0.60 0.20	5.0	1.600	0.20
(6)	6.0 7.0 8.0	0.30 0.40 0.30	7.0	0.800	0.10

Expected weighted value = 4.28

Variance of weighted value = 0.099

Results of arithmetic operations of this type give the decision maker an additional insight as to the variability of the final values. Whereas the calculations performed in the original additive weighting method provided only expected values, a measure of the probable dispersion of these values is now available. Various statistical methods can now be employed to permit further analysis of the choice being considered. Sensitivity of the resulting values to estimating variability may be investigated, and if data are available, certain assumptions pertaining to the use of standard statistical distributions may be made. Probably the most important benefit obtained from this type of analysis is the ability to utilize estimates of the extreme values which may result under actual conditions.

Methods Employing Utility Functions

The additive weighting model which incorporates discrete probabilistic data is valuable, but it can be refined to provide additional information. As with most improvements, the increase in available information is not free, both data collection and analytical procedures must be expanded.

The primary requirement for additional input data is the establishment of a continuum of attribute impact importance weights, or utilities, over the range of alternative performance values which may occur. Consideration of this relationship is essential as the relative impact of various levels of environmental disturbance may vary greatly over the feasible range of alternative operations. The classical additive weighting model does not consider this effect and thus the relative importance of impact is constant regardless of the operational performance of the alternative being evaluated. Inclusion of variability requires the introduction of a new data collection step in the evaluation procedure.

This new step is somewhat similar to the scaling technique employed earlier with the exception that the determination of relative impact requires two sets of data. First, each attribute requires a separate utility or scaling function describing the expected environmental impact for all feasible levels of attribute activity. Secondly, the levels of expected alternative performance must be estimated and these operational characteristics then transformed into a measure or corresponding impact.

An extension of the example problem discussed previously illustrates this procedure in simplified form. Originally the impact of various alternatives within the specific areas were stated in qualitative terms. These impacts were then scaled such that numeric values were available for use in later analyses. As an example, attribute three (Impact on Surrounding Air Quality) was described in terms of "high," "low," etc. It is now necessary to provide a metric for measuring the attribute level. In later sections, the possibility of having several measures for each attribute will be explored, but in this example, one will suffice. A measure such as "Thousands of Pounds of Particulate Matter per Year" will serve satisfactorily.

Determination of the realtionship between the descriptive attribute and the metric being utilized as a physical measure is now required. In developing such data, it is first necessary to determine the feasible range of the measurable criterion which may be experienced in the situation being investigated. The highest and lowest practically attainable feasible values are then used to establish the range of the metric along the abscissa of a set of Cartesian coordinates. The relative impact of various levels of the pollutant or other distrubance is then determined and plotted along the ordinate. In this case, a value of 1.0 being the worst possible condition and 0.0 representing negligible effect. Data from previous studies involved with the relative effects of pollutants and governmental regulations concerning limitations on environmental disturbance can sometimes provide guidelines for the development of such impact-scaling functions. However, in many cases it is necessary to employ subjective judgements in the form of expert opinions from personnel who are active in the area of study. This aspect of the data collection phase is discussed further in Chapter V.

The second step of the expanded data collection procedure is the development of probabilistic estimates of the expected performance of each alternative site-design combination. These estimates will be stated in terms of the criterion previously selected for the impact function, and will be based entirely upon projections of the alternative's physical operating performance. Conversion of this measure to one of impact will form the basis of the current evaluative procedure.

As shown in Figure 2, the probability density function of alternative performance levels are transformed through the utility function to provide a probability density function of expected impact. This transformation is well known for continuous density functions which are mathematically definable and can be accomplished through the use of the following procedure from Hahn and Shapiro (1968):

Let $f(x)$ = density function on the random variable x

y = $h(x)$ monotonic function of x.

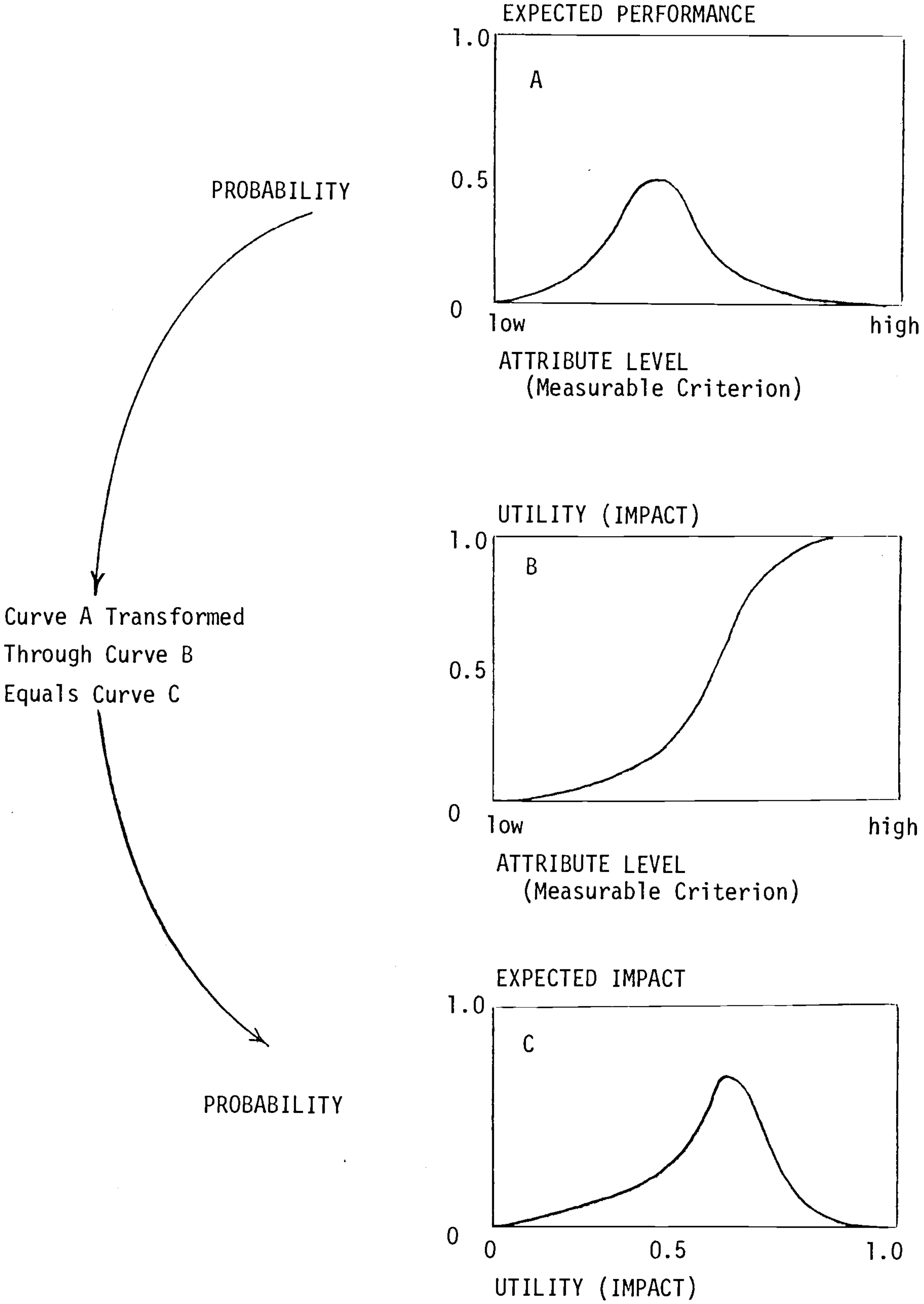


Figure 2. Transformation of Performance-Impact Relationships

The transformed probability density function resulting from the transformation of f(x) through the function h(x) is as follows:

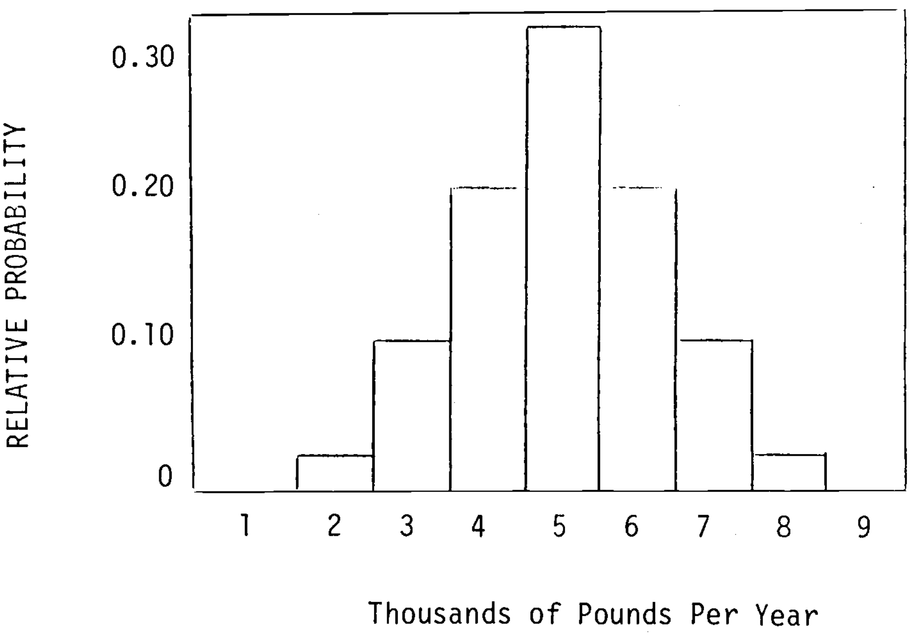
$$p(y) = f [x(y)] | \frac{dx}{dy} |$$

where x(y) is the inverse of the function h(x).

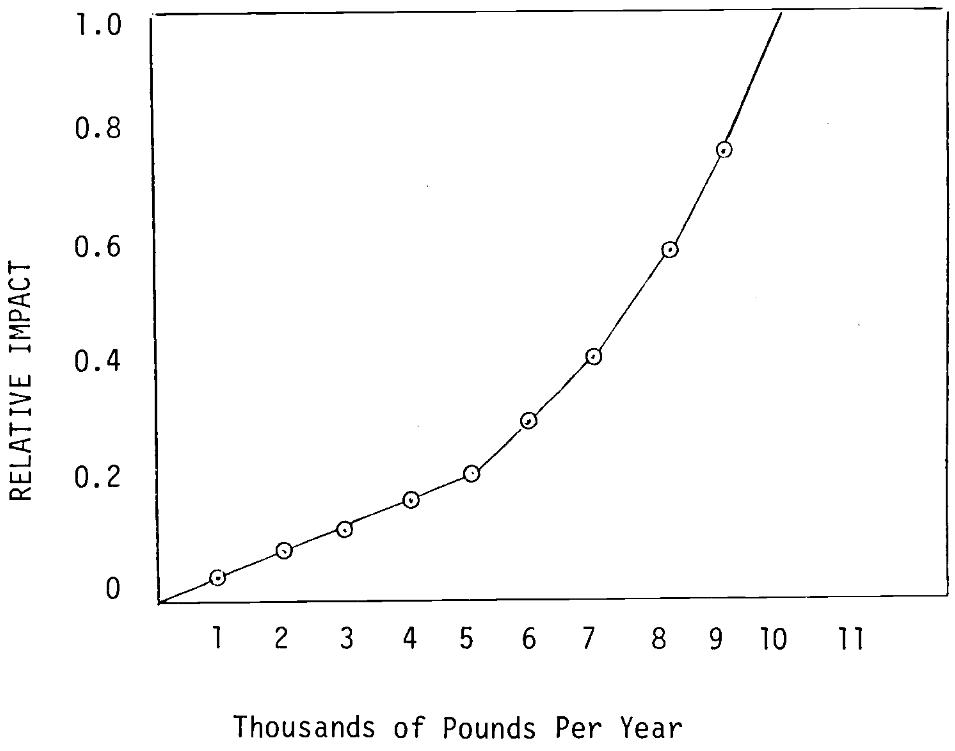
Since the data collected for the purposes described here are primarily discrete estimates, it will later be necessary to develop this transformation to utilize functions which are piecewise linear rather than continuous. This development will be discussed further in Chapter VI. However, a short example is provided to illustrate a direct arithmetic solution at this point.

In the situation under consideration, it is assumed that data have been collected on a subfactor involving the emission of some hypothetical airborne particulate. A graphical display of these data is shown in Figure 3. It should be noted that the distribution of probable performance characteristics is symmetrical while the impact scaling function is nonlinear in this particular case.

Results of a series of calculations utilizing these values are shown in Table VI. The statistical mean of the expected performance distribution is 5.0×10^3 pounds per year. In this case, a rather obvious value due to the summetry of the illustrative distribution. A form of point estimate of expected relative impact could be obtained by observing the impact scale value corresponding to the mean level of performance. Using this method, a value of 0.20 would be noted. However, such an approach not only omits any provision for using the available information on process variability but also usually results in an arithmetically incorrect value. Other than by chance, the only time this procedure will result in a correct value is when the distribution



(a) Expected Alternative Unit Performance



(b) Expected Impact Function

Figure 3. Input Data Forms For Hypothetical Airborne Particulate

of expected performance values is symmetrical and the associated section of the impact scaling function is linear. Under these conditions, the distribution of expected relative impact will also be symmetrical.

The results of applying the correct method of determining the expected relative impact is shown in column E of Table VII. The calculated value of 0.2356 differs from that obtained earlier because of the nonlinear impact function. By inspection, it is obvious that this difference would be even more pronounced if the performance distribution contained more variability. The skewness evident in the distribution of relative impact values (Figure 4) is a result of this nonlinear scaling function.

The estimated variance of the relative impact values is calculated in column F of Table VII. The usefulness of the variance as the only dispersion measure of the subfactor impact values is somewhat questionable as the resulting distributions often take widely varying forms. However, these subfactor variance estimates are valuable for the determination of an estimated aggregate impact variance.

The expected aggregate impact of any alternative under consideration is the arithmetic sum of the weighted attribute values. This relationship may be expressed as

$$\begin{array}{c}\text{Potential Environmental}\\ \text{Impact}\\ \text{(PEI)}\end{array} = \sum_{k=1}^{\ell} (W_k \cdot \overline{RI}_k)$$

where $\overline{RI}_k$ is the expected relative impact of the k^{th} attribute. Since the variance (σ_T^2) of the sum of a series of independent random variables is equal to the sum of the individual variances, it is possible to estimate the variance of the distribution of PEI values as

$$\text{Var(PEI)} = \sum_{k=1}^{\ell} (W_k^2 \cdot \text{Var}(RI_k)).$$

TABLE VII. SUMMARY CALCULATIONS FOR DETERMINING POTENTIAL IMPACT PARAMETERS

A Performance (10^3lbs/yr) x_k	B Probability $p(x_k)$	C $p(x)\cdot x_k$	D Relative Impact RI_k	E $RI\cdot p(x_k)$	F $p(x_k)(\overline{RI}-RI_k)^2$
1	0	0	0.04	0	0
2	0.04	0.08	0.08	0.0032	0.0009
3	0.10	0.30	0.12	0.0120	0.0013
4	0.20	0.80	0.16	0.0320	0.0011
5	0.32	1.60	0.20	0.0640	0.0003
6	0.20	1.20	0.30	0.0600	0.0008
7	0.10	0.70	0.42	0.0420	0.0034
8	0.04	0.32	0.56	0.0224	0.0042
9	0	0	0.76	0	0
Total	1.00	5.00 ($\overline{X}$)		0.2356 ($\overline{RI}$)	0.0121 Var(RI)

$$\overline{X} = \sum_{k=1}^{\ell} [p(x_k)\cdot x_k]$$

$$RI = \sum_{k=1}^{\ell} [p(x_k)\cdot RI_k]$$

$$Var(RI) = \sum_{k=1}^{\ell} [p(x_k)\cdot(\overline{RI}-RI_k)^2]$$

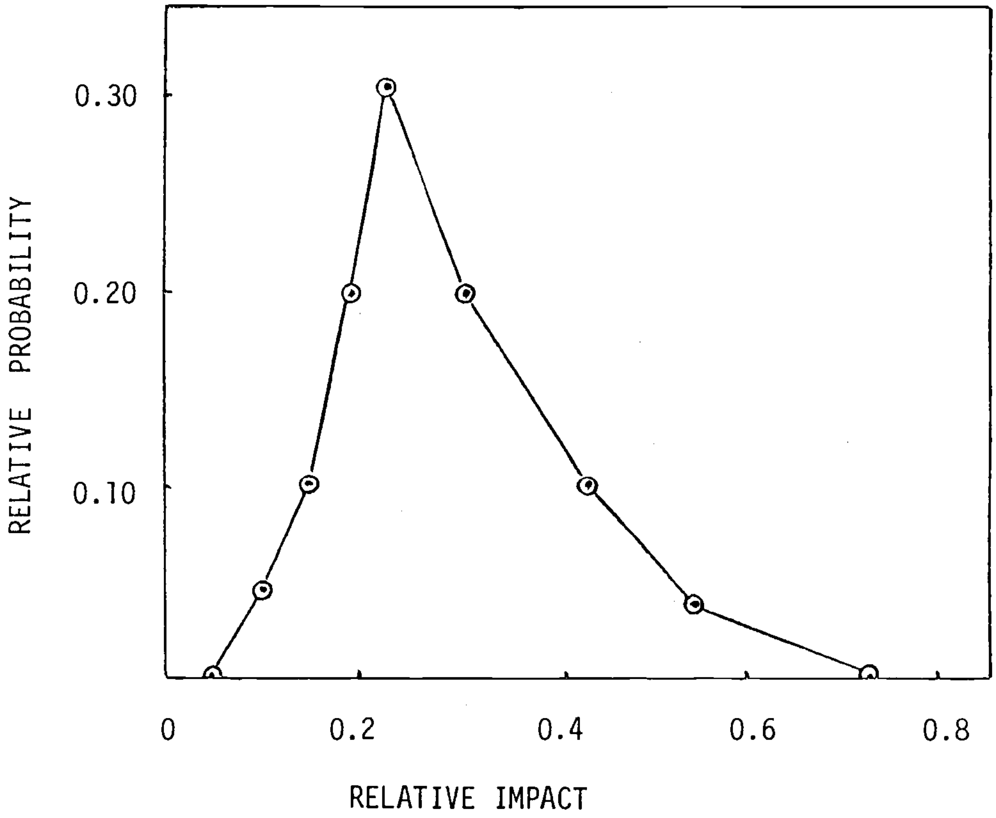


Figure 4. Results of Performance-Scaling-Impact Transformation

This relationship is particularly useful as it can be shown that the distribution of the sum of the series of random variables can be approximated by the normal distribution as the component population becomes larger (Brunk, 1965). These relationships are only exact when the component random variables exhibit complete independence. In the type of real world operations being considered, this condition of complete independence between subfactors is almost impossible to obtain. However, if care is exercised in the selection and definition of primary attributes and subfactors, the covariance effects may be minimized in the final model.

A graphical illustration representing the development of aggregate impact distributions is shown in Figure 5. The comparative potential environmental impact of each alternative is shown as the final result of the procedure. In situations involving several attributes, the arithmetic operations described previously become rather cumbersome. Additionally, there is a possibly significant loss of information. In order to minimize the effects while maintaining the advantages of the nonlinear additive weighting model, further development of the analysis technique is required. Discrete simulation methods utilizing piecewise linear functions to approximate nonlinear inputs are suggested. The feasibility of this technique depends somewhat on the input data and is investigated more fully in Chapter VI.

CONCLUSION

Classical additive weighting models provide a powerful technique for use in the analysis of certain multiple-alternative problems. However, the use of such models often results in a loss of information in

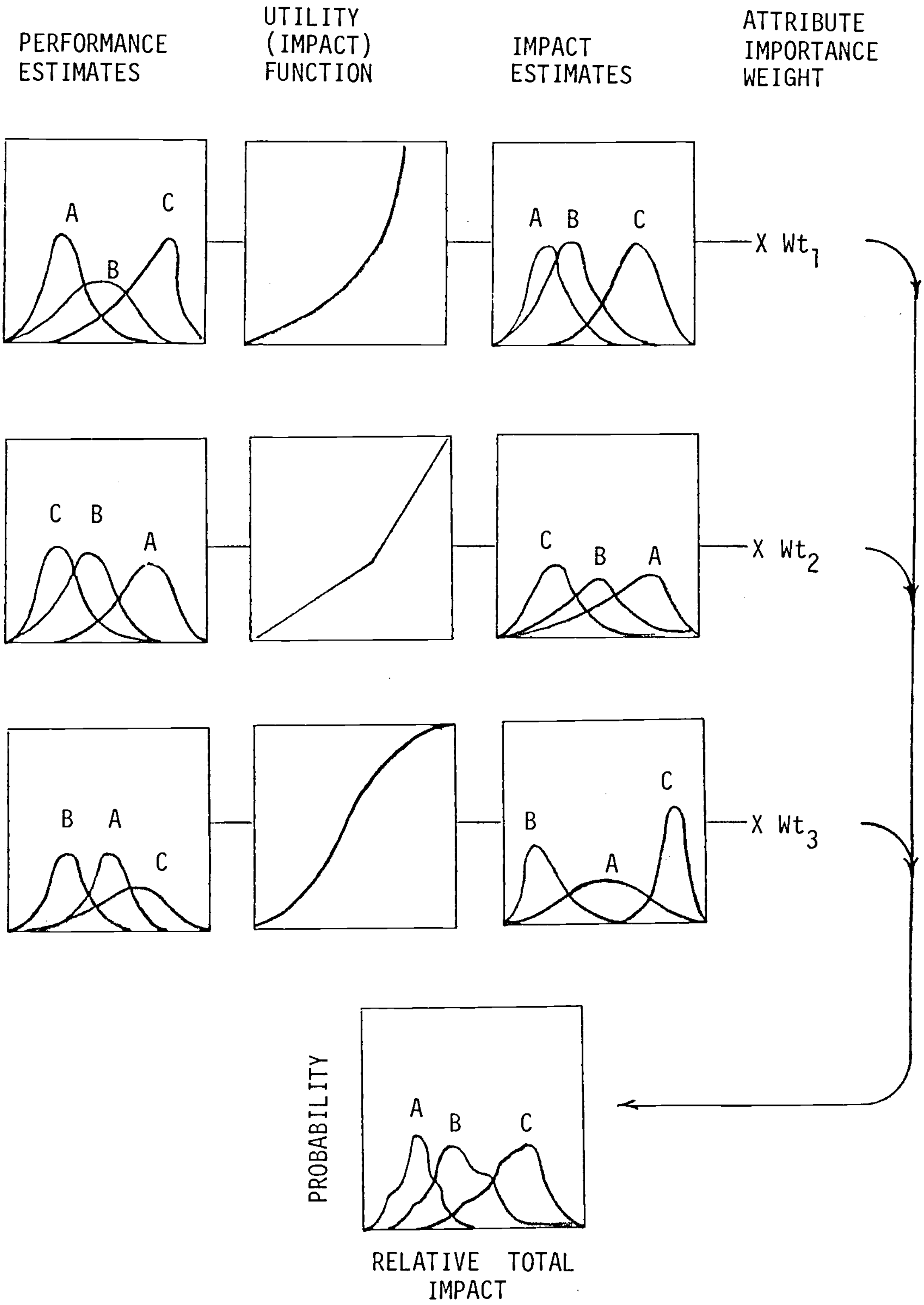


Figure 5. Development of Weighted Aggregate Distributions Through Performance-Impact Transformations

situations where performance variability is present in the alternatives being considered.

The utilization of models employing a limited number of discrete probability estimates is possible and computationally direct. Such models allow the inclusion of some variability and permit the determination of probable ranges of output values. However, they are not readily adaptable to the use of irregular continuous probability distributions, and they require direct estimates of the environmental impact resulting from alternative performance. This last requirement sometimes leads to erroneous assumptions because personnel familiar with the physical design are not knowledgeable about its environmental effects.

The use of a nonlinear model employing utility or impact-scaling functions alleviate this performance-impact transformation problem. However, the increased detail of such models requires the collection of additional data and the development of more involved analytical techniques. Discrete arithmetic computations provide estimated values for the mean and variance of aggregate alternative impact, but are rather cumbersome and lack sufficient flexibility for many sensitivity studies. The desirability of applying simulation methods to the evaluation procedure depends upon the forms of data collected, and will be investigated later in this paper.

V. DATA COLLECTION

Preceding sections discussed in some detail a procedure for the incorporation of nonmonetary factors into the siting analysis process. However, before these procedures can be implemented, sufficient quantities of valid input data must be collected. This chapter is directed towards the development of a general method of data collection and analysis.

As seen previously, an accurate evaluation of the expected total environmental effect requires projections not only of absolute attribute impact, but also of the importance of that impact at a particular geographic location. It is obvious that in estimating factors involving a wide range of possible effects an equally wide range of expert opinions is a necessity. To collect and organize the required data, the following stepwise series of operations has been developed:

1. Develop a suitable list of primary attributes for the various site-design alternatives under consideration.
2. Develop importance weightings for each of the primary attributes.
3. Subdivide primary attributes into measurable criteria subfactors.
4. Allocate primary attribute importance weighting among subfactors.
5. Develop a utility or impact-scaling function for each subfactor.
6. Determine an expected unit performance distribution for each subfactor.

Each of these steps will be discussed in the following sections of this Chapter.

Development of a Suitable List of Primary Attributes

The development of a suitable list of primary attributes, and later a list of subfactors which are quantifiably measurable, is a key part of the overall evaluation process. As stated earlier, it is assumed that the geographic area of the country will influence in some degree the factors selected. For instance, it is obvious that consumptive water usage would be more important in arid areas, than in the Southeastern United States, and that the effect of a particular location on large urban areas would be of greater concern in New Jersey than Montana. The more obvious regional differences are somewhat accounted for in the factor weighting procedure, but the key point at this stage is to develop a list of attributes which is representative of the region under consideration.

To facilitate this task, a questionnaire can be developed in which respondents may add or delete attributes as they wish. Persons knowledgeable in the various engineering, environmental, and social areas are invited to participate in updating and adding to or deleting from the attribute list. Additionally, knowlegeable individuals from diverse interests and citizen groups may also participate at this stage. Care must be taken, however, to insure that the factors listed are meaningful and valid for the purposes of developing a comparative evaluation. It again must be emphasized that procedure being developed in this example is for the comparison of siting alternatives and not for the determination of the social, ethical, and possibly moral ramifications of increasing the supply of electrical power to the public.

The starting point for any regionally based questionnaire is a listing of factors involving general impact on air, land, and water and the various lifeforms therein. A generalized listing of these factors is shown in Figure 6. Those involved in completing the questionnaire must be made fully aware of its purpose and how their input is to be used before starting to work on it. Examples of the types of primary attributes are furnished as part of the list and, as more contributed opinions are collected, this example list can be modified and extended.

It should be made clear to those participating that these attributes or characteristics are usually nonmonetary in nature and are to be only the most important classifications in a system which will later be subdivided into specific measurable subfactors. At this point care must be taken to assure that the various operational attributes are well-defined and free of overlap or redundancy. That is, the list should contain only mutually exclusive factors such that the double counting of impacts and the problems of statistical non-independence be minimized (Fishburn, 1964).

The termination point in the listing procedure is somewhat subjective as the process could continue indefinitely. In dealing with a finite sampling population, such as a Board of Directors or Siting Committee, the limits are naturally finite. However, in decisions made with public scrutiny and input, the listing process could be long and time consuming. It is important that persons familiar with the natural and social composition of the region have an opportunity to contribute, but a reasonable deadline must be set for the completion of the contri-

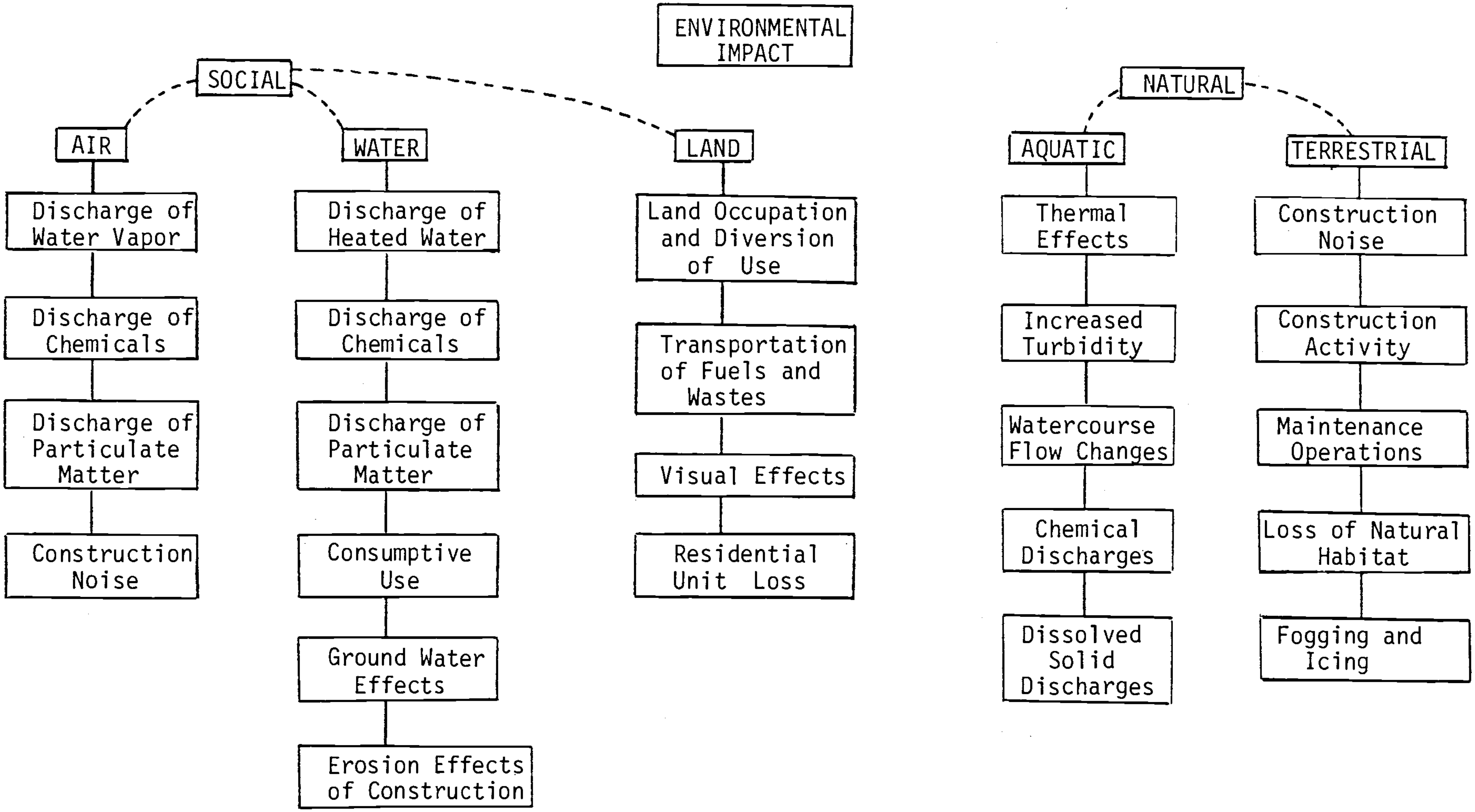


Figure 6. Generalized Possible Environmental Effects of Construction and Operation

bution.

As was discussed earlier in Chapter II, the procedures being developed in this paper are illustrated in part by data collected for the construction and operation of a two-unit nuclear power plant located in the Southeastern United States. Various personnnel from the constructing utility, regulatory agencies, and the Oak Ridge National Laboratory were asked to contribute factors for inclusion as regional primary attributes. The composite list resulting from these inputs is given in Table VIII.

Development of Importance Weighting For Each of the Primary Attributes

This step of the data collection process involves the development of a scale for measuring the relative importance of previously determined primary attributes. Several techniques are available for developing a scaled based upon judgemental or subjective opinions (Bartlett, Heerman and Rettig, 1960; Eckenrode, 1965). Five methods which may be considered are as follows:

1. Ranking: The judge is asked to place a numerical rank next to each attribute, indicating by 1 the highest ranking, by 2, the next highest and so forth. This method is similar to the lexiographic procedure described in Chapter III.
2. Rating: The attributes are listed next to a continuous scale 0 to some high value (10 is used in Chapter III) and the judge is asked to draw a line from each attribute to any appropriate value on the scale. Any position on the scale is valid, and more than one attribute can have the same value.

TABLE VIII. PRIMARY ATTRIBUTES DESCRIBING ENVIRONMENTAL EFFECTS

Aesthetic Impact of Plant Features

Changes in Abundance and Diversity of Wildlife Species

Consumptive Use of Water

Discharge of Detrimental Substances into Atmosphere

Discharge of Detrimental Substances into Surface Water

Discharge of Heated Water into Surface Water

Discharge of Water Vapor into Atmosphere

Effects on Ground Water

Erosion Effects of Construction

Extended Effects on Area Socioeconomics

Influence on Commercial Harvests of Wildlife Species

Land Occupation and Diversion of Use

Plant Operations and Maintenance Activities

Socioeconomic Impact of Construction Force

Transportation of Fuels and Waste

Water Intake System Effects

3. Partial Paired Comparison:

(a) Matrix Method: The attributes are presented on the ordinate and the abscissa of a partial matrix as illustrated below.

ATTRIBUTE

ATTRIBUTE

	1	2	3
4			
3			
2			

The judge is then asked to indicate in each block which of the attributes are considered more important. Ties between attributes are generally not permitted, and thus a choice is forced in all cases. Attributes are thus ranked on the basis of "wins" in the comparative procedure (Buel, 1960).

(b) Index Method: Each attribute is paired once with each other attribute and each pair listed on a separate sheet of paper or index card. These pairs are then presented to the judge one at a time in random order. The judge selects the most important of the attributes and it is so recorded. At the completion, attributes are again ranked based upon the number of "wins" they have obtained.

4. Complete Paired Comparisons:

This method is the same as the index method of partial paired comparison except that each attribute is paired with each other attribute two times with the order of presentation reversed. This method takes approximately twice as long to complete, but has the advantage of at least partially eliminating positional bias on the part of the judge.

5. Churchman-Ackoff-Arnoff Method:

   In this method introduced by Churchman, Ackoff, and Arnoff (1957), the list of attributes is presented to the judge who then executes the following stepwise procedure:

   (a) Rank the criteria in order of importance as described in method (1).

   (b) Tentatively assign a value of 1.0 to the most important attribute (F_1), and assign other values (F_i) between 0 and 1.0 to the other attributes based on the ranked position.

   (c) Decide if the attribute with value 1.0 (F_1) is more important than all the other attributes combined. If so, the other attribute values must be adjusted such that $V_1 > \sum_{i=2}^{n} V_i$. If F_1 is equal in value to the other attributes, then the values of the remaining attributes must be adjusted such that $V_1 = \sum_{i=2}^{n} V_i$. If F_1 is less important than the whole of the remaining attributes then their values must be adjusted such that $V_1 < \sum_{i=2}^{n} V_i$.

   (d) Using the value of V_2 finally selected in step (c), the procedure is then repeated keeping V_2 constant and performing the comparison with the remaining N-2 attributes.

(e) The method is continually employed until N-1 criteria have been evaluated and their final values tabulated.

Interesting extensions of this technique, including development of the ordinal preference procedure as a linear programming formulation are possible. A more complete discussion of the basic procedure is available in Ackoff and Sasieni (1968) and extension utilizing optimization techniques are developed by Riggs and Inoue (1975).

A number of studies have been performed in analyzing the consistency of results obtained through the application of these ranking methods. A general survey of this work indicates that there is a high degree of reliability among the methods in producing the same ordering of attributes (Bartlett, Heerman and Rettig, 1960). However, most of this work utilizes the Kendal Coefficient of Concordance as the statistic for testing differences in order, and thus interval magnitude between selections was not considered.

Comparative ranking, rating, and the index approach to partial paired comparison are the methods most often used in studies involving the ordering of attributes. Early work by Mosteller (1951) and Rummel (1964) proposed the development of reliable interval scales utilizing the paired comparison technique. Further work in comparing the three basic techniques showed that the ranking method was generally preferred when less than five attributes were to be scaled, but the rating method (while simple to apply) often exhibited the undesirable characteristics of narrow overall range and large mean deviation (Eckenrode, 1965). Additional work by Dunn-Rankin and King (1969) produced a methodology for easily applying the partial paired comparison technique to the development of a simplified rank method of scaling. In addition to comparing favorably to the accuracy of other techniques, this method possesses the following desirable characteristics:

1. It allows continuum scaling of attribute values with meaningful end point.
2. Extreme frequencies, i.e. 0.0 or 1.0 are permitted in the chance occurrence of total agreement on the complete superiority or inferiority of an attribute.
3. It allows tests of significance to be made between attributes.
4. Sample size requirements for various levels of confidence may be calculated.
5. It produces a ratio scale of attribute importance weights which is required for arithmetic operations involved in the alternative evaluation procedure.

In order to more fully examine the simplified rank method of scaling, a short example utilizing the hypothetical location data introduced in Chapter III will be considered. The numerical calculations are not complex, and will thus be carried on stepwise throughout the discussion.

Earlier in this paper, relative factor importance weightings were arbitrarily assigned to the six environmentally significant attributes of the illustrative problem being considered. The Dunn-Rankin procedure will now be employed to show how group inputs may be used to develop reliable weighting factors. The attributes to be considered are as follows:

ATTRIBUTE	CODE
Land Requirements	A
Consumptive Water Use	B
Impact on Area Aquatic Life	C
Impact on Adjoining Land Use	D
Impact on Surrounding Air Quality	E
Aesthetic Impact	F

The problem to be considered involves the ranking of these attributes based on the reactions of a group of judges. In this example, 60 judges are to be considered. Further comments pertaining to the significance of sample size will be made in the discussion of Step 4.

Step 1. The attributes are presented to the judges for comparison in a standard randomly ordered partial paired-comparison procedure. Results are then tabulated in the matrix form illustrated in Table IX (a). These values are then reordered into the form shown in Table IX (b), the only change being that the attributes have been rearranged in order by the number of dominant responses.

Step 2. Rank sums, rank totals, minimum, and maximum ranks are then calculated, where:

Rank sum for column j, (R_j), equals the total responses in the column plus the number of judges (N=60). Thus, the following results were obtained.

TABLE IX. RESPONSES FOR SIMPLIFIED RANK-SCALING EXAMPLE PROBLEM

(a) Original Data*

ATTRIBUTE	A	B	C	D	E	F
A	-	48	57	36	51	24
B	12	-	48	18	42	9
C	3	12	-	9	15	0
D	18	42	51	-	48	18
E	9	18	45	12	-	6
F	36	51	60	42	54	-
TOTALS	84	171	261	117	210	57

(b) Reordered Data

ATTRIBUTE	F	A	D	B	E	C
F	-	36	42	51	54	60
A	24	-	36	48	51	57
D	18	24	-	42	48	51
B	9	12	18	-	42	48
E	6	9	12	18	-	45
C	0	3	9	12	15	-
TOTALS	57	84	117	171	210	261

*Note: Values shown (a_{ij}) indicate a preference of $a_j > a_i$ where i = row and j = column.

ATTRIBUTE	B	D	A	C	F	E
Total Responses	57	84	117	171	210	261
+ Number of Judges (N)	60	60	60	60	60	60
Rank Sum (R_j)	117	144	177	231	270	321

$$\text{Rank Total} = \sum_{j=1}^{6} R_j = 1260$$

The tabulation totals can be checked at this point by applying the equality $\sum_{j=1}^{m} R_j = (N)\ (M)\ (M+1)/2$, where M equals the number of attributes being considered. Thus,

$$1260 = (60)\ (6)\ (7)/2$$
$$= 1260.$$

Other values of importance are

$$R_{min} = N = 60$$

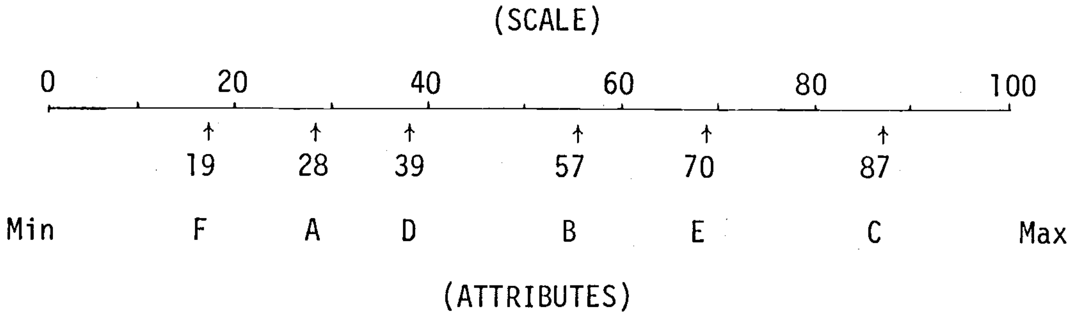
$$R_{max} = (N)\ (M) = (60)\ (6) = 360$$

$$\text{Range} = R_{max} - R_{min} = 360 - 60 = 300$$

Step 3. Scale scores may then be calculated using the following format:

Attribute	R_j	$R_j - R_{min}$	$\frac{R_j - R_{min}}{\text{Range}} \times 100$
Minimum	60	0	0
F	117	57	19
A	144	84	28
D	177	117	39
B	231	171	57
E	270	210	70
C	321	261	87
Maximum	360	300	100

Step 4. The results may now be shown on an initial scale as



At this point, it must be emphasized that this procedure provides only a statistical approximation of a ratio scale. As would be expected, the statistical validity of the results varies with the number of raters employed and the distribution of values on the final scale. Obviously if all the values were perceived as being of nearly equal importance the results would be clustered around a value of 50, and if the judges were in perfect agreement as to the ranking of the attributes, the values would be distributed at equal intervals along the scale.

It is possible to treat this situation in a manner similar to that where several sample means are tested for significant differences. The hypothesis in this case being that the weights $\mu_A = \mu_B = \cdots\mu_F$ are equal, being tested upon the observed means R_A, R_B, etc. This hypothesis may be tested by the use of the range, W, as a measure of the dispersion of the j means. A test of hypothesis of equal means can thus be made by comparing the range of the means to the within-groups sum of squares. This can be done with the appropriate value of Harter's test statistic $Q_a = W/S$, where $S = S_p/\sqrt{n}$ and S_p^2 is the pooled or within-groups mean square and n is the size of each sample. This value of $S_p/\sqrt{n}$ is an estimate of $\sigma/\sqrt{n}$, the standard deviation of X's (or R_j's) for samples of size n from the same population. Thus give n a value of Q_a, an estimate of the required minimal sample size can be obtained.

Values of Q_a are available from the tables developed by Harter (1959) or from Dixon and Massey (1969). The appropriate value is then applied to the relationship $N = Q_a^2 (M) (M+1)/12$ as obtained from Dunn-Rankin and King (1969). The value of N thus obtained is adequate to insure that enough samples are taken to provide each item with the opportunity to demonstrate a significant difference from each other item. For M = 6 attributes, the required value for $Q_{0.05} = 4.030$ and $N_{min} = (4.030)^2 (6) (7)/(12) \doteq 57$. Thus adequate sampling has been performed to obtain a valid estimate of the perceived importance weights. Further discussions of the statistical tests for determining intervals of significant differences between values are available in Dunn-Rankin (1965).

Step 5. The final step of the procedure is to develop normalized importance rankings for use in the evaluation procedure. This is accomplished by summing up the previously obtained scale values and dividing each by the total.

Attribute (A_i)	Value	Importance Weight (W_i)
F	19	0.063
A	28	0.093
D	39	0.130
B	57	0.190
E	70	0.233
C	87	0.290
	300	0.999

Applying this technique to the previously obtained list of primary attributes allowed the development of the normalized importance weightings shown in Table X. Development of a scale such as this requires a considerable amount of time and resources. For instance, the paired comparison procedure for analyzing 16 attributes requires that 150 comparisons be made by each judge or rater, and people with sufficient knowledge of the study project are often difficult to locate. For this reason, the results shown in Table X are based on a reduced sample of 27 raters. Of necessity, these results will be applied to the evaluation techniques presented in the remainder of this paper. The collection and computational procedures used are, however, the same as that which would be employed if more resources were available.

Subdivision of Primary Attributes Into Measurable Criteria Subfactors

The next step in the evaluation procedure is the development of a series of factors for measuring the various categories of impact encompassed by each of the primary attributes. A level of effect may require the use of a composite grouping of several subfactors, each of which has an individual criterion. While some of the primary attributes appear as totally qualified in nature, and thus difficult to measure in objective terms, their total effect can usually be determined by a series of quantitative subfactors. It is these subfactors and their representative units of measure which must now be established.

In selecting the subfactors to be employed, an attempt should be made to meet the following requirements:

1. There should be a strong, easily seen relationship between the primary attribute and its various subfactors.
2. The subfactors should be well-defined and as independent as

TABLE X. NORMALIZED RANK SCALING OF ATTRIBUTE IMPORTANCE

Rank Order of Importance	Factor Weights, X_i	Normalized X_i
Discharge of Detrimental Substances into Water	81.03	.1013
Discharge of Detrimental Substances into Atmosphere	80.1	.1001
Discharge of Heated Water into Body of Water	61.1	.0764
Transportation and Storage of Fuels and Waste	59.22	.0740
Socioeconomic Impact of Construction Labor Force	52.1	.0651
Effects on Ground Water	51.14	.0639
Discharge of Water Vapor into Atmosphere	49.75	.0622
Water Intake System of the Plant	46.77	.0585
Effect on Socioeconomic Well-Being	45.13	.0564
Consumptive Use of Water	44.46	.0556
Changes in Abundance and Diversity of Wildlife Species	44.22	.0553
Plant Operation and Maintenance Activities	40.75	.0509
Erosion Effects of Construction	40.03	.0500
Influence on Commercial Harvests of Wildlife Species	39.6	.0495
Land Occupation and Diversion of Use	38.2	.0478
Aesthetic Impact of Plant Features	26.36	.0330
	799.96	1.0000

possible under realistic operating conditions.

3. The ease with which interested parties can see the applicability of the criteria in a real-world environment should not be understated.
4. The consideration of cost and difficulty involved in measuring the quantifiable factors is an absolute necessity if the economic viability of the evaluation procedure is to be maintained.

The utilization of judgements obtained from experts working in the various descriptive areas is an integral part of this subfactor determination process. Not only can they provide information on the various relationships and measurement procedures directly involved with the study, but often can cite the strengths and weaknesses of previous work in related types of measurement activities.

An example of such assistance can be found in the case of the attribute "Consumptive Use of Water". Original engineering estimates were made in terms of acre-feet per year. However, after consultation with planners in this area, it was found that the percent change in availability to other potential users was a preferred measurement unit. In this case, the primary attribute is represented by a single subfactor resulting in the following relationship:

Primary Attribute	Subfactor	Measurement Unit
Consumptive Use of Water	Reduction in Surface Water Supply	Percent Change in Availability to Potential Users.

A much more complex attribute would be one of those concerned with atmospheric pollution. In a case such as this, the determination of total effect would involve the use of several subfactors and can take the following form:

Primary Attribute	Subfactors	Measurement Unit
Discharge of detrimental substances into the atmosphere	A. Chemical Pollutants-nitrogen oxides	ppm
	B. Chemical Pollutants-hydrocarbons	ppm
	C. Chemical Pollutants-carbon monoxides	ppm
	D. Chemical Pollutants-sulfur oxides	ppm
	E. Radionuclides	man-rem/year
	F. Non-Radioactive particulate - ash	mg/m^3

The advice of technical experts is most helpful in the establishment of complex composite groupings. The analyst gathering needed data should always attempt to obtain collective judgements from several qualified personnel in order to minimize any effect of bias resulting from personal and professional factors. The subfactor-measurement unit list finally developed from such an interactive multiple opinion process should then be shown to all concerned parties for comment and possible correction before the data collection phase proceeds further.

Allocate Critical Attribute Importance Weightings Among Subfactors

It is now necessary to assign individual importance weightings to each of the subfactors selected in the previous steps of the procedure. Naturally, the sum of these individual weightings must equal the weighting assigned the primary attribute which they comprise. Several of the weighting methods described previously can be considered for application at this point. It is likely that all of those mentioned could be used successfully depending somewhat on the conditions of employment. However, due to the small number of subfactors to be considered within each attribute, the simpler techniques such as rating and ranking would probably serve adequately.

A modified version of the basic rating procedure has been developed for use in water resources planning and with minor adaptations lends itself to the problem of subfactor weighting (Battelle Columbus, 1972). This procedure allows the stepwise comparison of ranked subfactors with the additional provision that candidate subfactors may be weighted very close together or even equal. While this capability is available with the rating procedures, it is not carried through systematically.

In determining the individual subfactor weightings, the judges involved are asked to consider the following:

- The inclusiveness of the criteria in describing the primary attribute.
- The reliability of the criteria measurements.
- The sensitivity of the criteria to changes in facility design and operating conditions.
- The sensitivity of the criteria to changes in the environment.

It is highly possible that the judges involved may feel that the criteria are of equal or very nearly equal importance. If this is the case, then each of the n subfactors are equally weighted by simply dividing their primary attribute importance weighting by n. In situations where this is not the case, the following procedure may be employed:

1. Rank the subfactors in decreasing order for the primary attribute being evaluated.
2. Assign a value of 1.0 to the highest ranking subfactor, and then compare the second ranking subfactor to the highest. Determine the relative importance of the second to the first and

express this value as a decimal ($0 < RI_2 < 1.0$).

3. Continue this stepwise comparison of subfactors until all have been evaluated with reference to the next most important subfactor.
4. Determine relative importance weightings by multiplying out decimal equivalents, summing and normalizing based on the sum.
5. When more than one judge is involved, average the various importance weights derived by all the individuals.
6. Multiply the average values by the weight of the primary attribute.
7. Indicate to all participating judges the results of the weighting procedure. If significant differences exist, it may be necessary to repeat the experiment after discussion of these differences.

For a numerical example, assume that four subfactors (A, B, C, D) have been selected.

These subfactors are then ranked

First	B
Second	D
Third	A
Fourth	C

and relative importance weightings are assigned.

B = 1.0

D = 0.6 of B

A = 0.4 of D

C = 0.5 of A

Multiplying these relative weights gives the following results:

B = 1.0

D = 0.6 x 1.0 0.60

A = 0.4 x 0.6 0.24

C = 0.5 x 0.24 0.12

Total 1.96

Subfactor importance weightings are thus,

B = 1.00/1.96 = 0.51

D = 0.60/1.96 = 0.31

A = 0.24/1.96 = 0.12

C = 0.12/1.96 = 0.06

1.00

These normalized subfactor weights are then multiplied by the weight of the corresponding primary attribute obtained earlier. If the primary attribute had a scaled importance ranking of 0.14, the approximate relative importance of each subfactor would be:

Subfactor B 0.51 x 0.14 = 0.0714

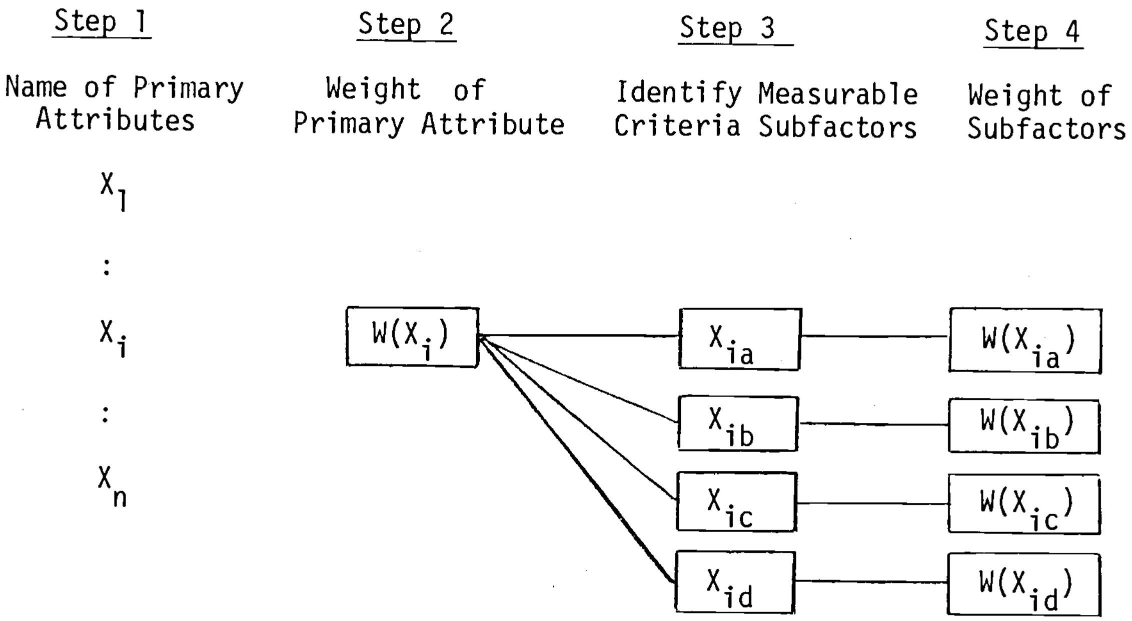
D 0.31 x 0.14 = 0.0434

A 0.12 x 0.14 = 0.0168

C 0.06 x 0.14 = 0.0084

0.1400

At the completion of the first four steps of the impact evaluation procedure, the steps could be represented as follows:



Development of Utility or Impact-Scaling Functions For Each Subfactor

The steps leading to the determination of subfactor-criteria weights are not essentially dissimilar to those followed in many evaluation problems. The remaining two phases of data collection are somewhat unique in that expert judgements are obtained in the form of density functions rather than point estimates.

The next step is the development of utility or scaling functions encompassing the entire feasible range of outcomes for each subfactor. These functions will then be employed to transform values of the various impact criteria to dimensionless measurement scales which will relate how much the value of a specific impact criterion varies within its feasible range. Through the use of this technique, it is possible to develop an aggregate site value which heretofore would have involved the summing of the numerous, dissimilar units of measurement. However, care must be exercised at this point, for by reducing criteria measurements to a single dimensionless scale of value, a compromise in descriptive accuracy could result. This potential problem can be minimized if the planners utilizing the final resulting value participate in the development of the study to assure their awareness of the methods employed in developing the numerical values.

In developing utility functions, it is first necessary to define the best possible condition which may exist in the operating environment, and then identify the worst permissible condition which may occur. These values are then recorded as the limits on the abscissa of a set of Cartesian axes. The value of the function to be developed is recorded on the ordinate with scale values bounded by (0,1). Traditional utility or value functions are drawn such that the least favorable condition has an ordinate value of 0.0 and the most desirable feasible condition a value of 1.0. To illustrate this concept, two hypothetical functions are shown in Figure 7. As an example, the "beneficial" criterion could be "Dissolved Oxygen in Outlet Water", while the "unfavorable" criterion could be "Noise Level at Property Boundary".

While the concept of developing a descriptive function such that a value of 1.0 represents a highly desirable circumstance is often employed, the procedure currently being developed requires the use of a reversed scale of desirability. That is a graphic relationship where a value of 0.0 represents minimal environmental impact and thus is a desirable indicator. This change is due to the need for developing a measure of aggregate impact which represents the sum of a series of weighted component impacts. The basic formulation of the type of nonlinear additive weighted model was presented earlier in Chapter IV and illustrates how the relative impact scaling functions are to be used.

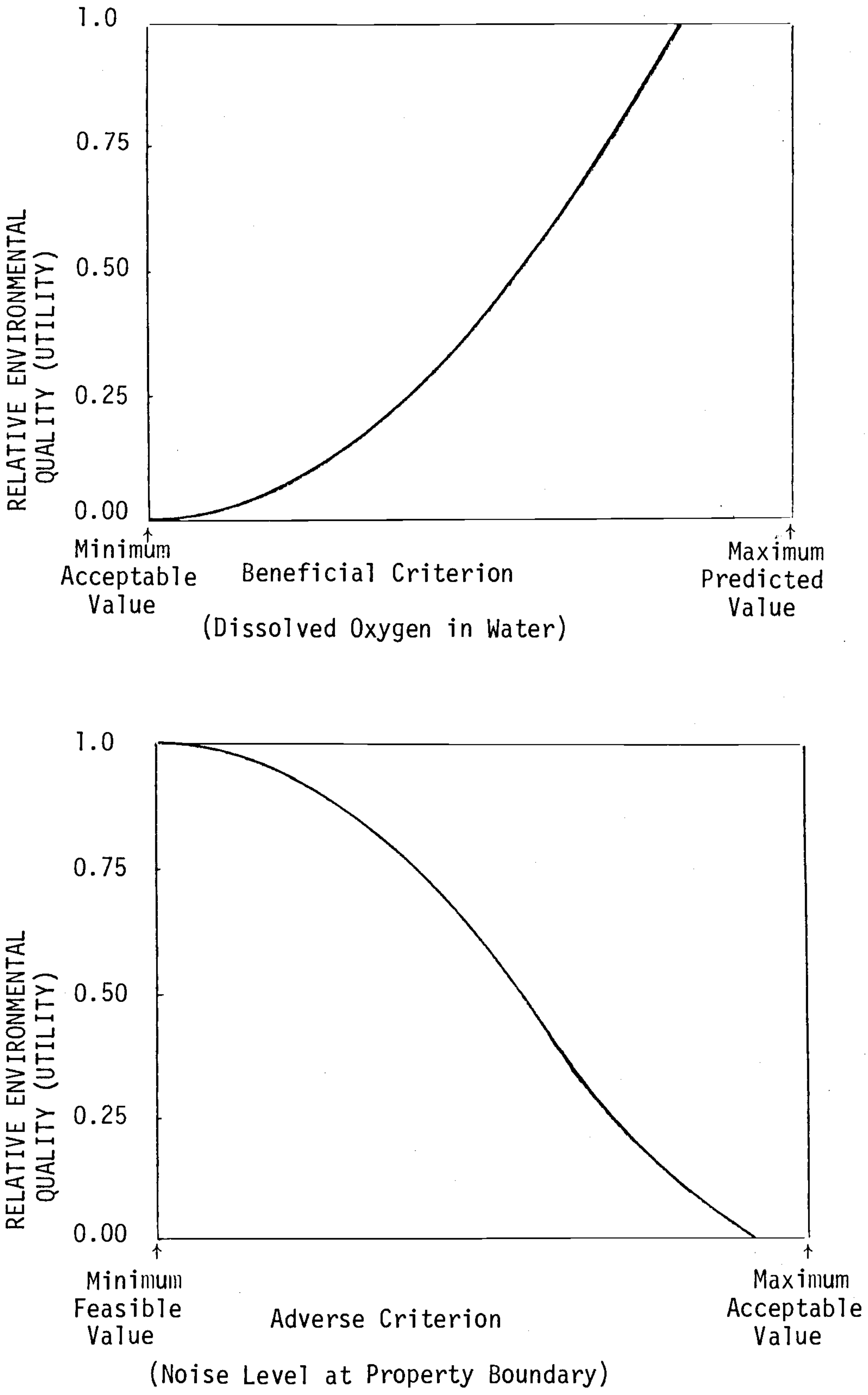


Figure 7. Representative Utility Functions Illustrating Hypothetical Criteria

Relative impact functions can be developed directly or obtained through the transformation of data which may presently be available in the form of a utility indicating the measure of relative environmental quality. The conversion of data from a function describing environmental quality to one of environmental impact is very simple. The impact function values for specific levels of the measurement criterion are equal to 1.0 minus the corresponding utility value for environmental quality.

The quality/impact relationship for a standard example of environmental factor, "Available Dissolved Oxygen in Water", is shown in Table XI. In this sample data from Battelle Columbus (1971), the relationship between dissolved oxygen and the overall level of environmental quality corresponds primarily to the support of aquatic life.

TABLE XI. RELATIONSHIP OF AVAILABLE DISSOLVED OXYGEN TO RELATIVE ENVIRONMENTAL QUALITY AND IMPACT MEASUREMENT

(I) Level of Dissolved Oxygen (mg/ℓ)	(II) Relative Environmental Quality Value	(III) Relative Environmental Impact Value
0	0.00	1.00
1	0.05	0.95
2	0.10	0.90
3	0.15	0.85
4	0.25	0.75
5	0.50	0.50
6	0.75	0.25
7	1.00	0.00

The data in columns I and II indicate the relative amount of aquatic life which can be supported under varying conditions of oxygen saturation. In other words, water containing 4.0 mg/ℓ of dissolved oxygen is only valued at 0.25 or one-fourth the life support capability of water containing 7.0 mg/ℓ of dissolved oxygen.

Relative environmental impact values determined from the transformation of the data in column II are presented in column III. Obviously, a dissolved oxygen level of 0.0 mg/ℓ would result in a severe impact on aquatic life. Conversely, oxygen levels of 7.0 mg/ℓ and higher would result in negligible impact and thus are assigned a relative value of zero.

In the development of such descriptive functions, it must be realized that in any situation, available technology, cost, resource constraints, and the characteristics of the natural environment will render certain outcomes feasible. Care must be taken to insure that the limits set are not excessively wide or restrictingly tight. Limits which are too narrow will likely be exposed when expert judgement is called upon for the completion of the utility function, but occasionally, respondents will attempt to make their reply fit the given parameters thus leading to erroneous results. The primary difficulty resulting from unrealistically wide limits is that large amounts of unneeded and misrepresentative data are developed, thus inhibiting the manageability of the analysis.

Data pertaining to the development of utility or impact-scaling functions are available from a number of sources, but in many instances must be obtained directly from personal interviews with person knowledgeable in the area of study. Various method of obtaining expert opinions in the form of scoring or utility functions have been studied. Techniques involving forced choices between measurement ranges (Comrey, 1950) and the use of constant-sum, paired-comparisons (Torgerson, 1958) are useful if a large number of judges are available for each criterion. However, when the number of judges is limited and the questions involved are primarily technical in nature, the semi-subjective, based on experience, graphical technique provides generally satisfactory results. Tests of several judges using this technique to construct the utility function of a common environmental quality standards have shown close correlation in results (Battelle Columbus, 1971). Graphical methods were thus employed in obtaining many of the impact-scaling functions for the subfactors developed earlier.

Determine Subjective Unit Performance Distribution For Each Subfactor

The final step in the data collection phase of the evaluation procedure is the development of estimates of outcomes resulting from the construction and operations of a specific plant at a specific site. Whereas data collected up to this point have represented the range of possible impact which could result from construction and operation, the specific site-design alternatives resulting in various levels of impact have been omitted. This omission is by design, as the primary goal of the procedure is to permit the evaluation of various proposed site-design alternatives using a consistant impact measuring scale. Elements of the scale are now complete and it is necessary to obtain estimates dependent upon plant design.

Prediction of outcomes for criteria characterizing the impact of a specific engineering design is naturally a somewhat uncertain process.

Personnel involved in the design, construction, and operation of a specific plant are generally concerned with the technical elements of the alternative under consideration. Their background and training place them in a position where design criteria such an Intake Feedwater Velocity and Outlet Water Temperature are more familiar than Fish Species Impinged or Aquatic Effects of Thermal Shock. The first two factors are design parameters and the latter pair are environmental effects. Dissimilarity of measurement scales is the reason for the development of utility or scoring functions in the preceding section. Employment of utility functions will allow the conversion of engineering design estimates to relative impact measurements for a specific alternative.

While engineering design proposals usually specify expected outcomes, it must be realized that often great variability is inherent in the operation of a finished piece of equipment. Even when the design under consideration is similar or perhaps identical to those previously used, variability in operating parameters, material inputs, operator training, and the natural environment will result in a range of possible outcomes. In the consideration of power plant designs, the inclusion of this variability is especially crucial as an analysis of a problem involving future operations cannot be realistically made using only most likely values.

The development of functional estimates describing projected outcomes from future operations requires a combination of objective and subjective probabilities. Objective probabilities are those evolved from observing the outcomes of an oft repeated experiment. Subjective probabilities are a measure of a judges' personal belief in the particular outcome of an experiment which has yet to be performed.

Classical statistical theory is generally concerned with the development of objective probabilities. However, in recent years, considerable attention has been given to the problem of assigning subjective probabilities to the possible results of future events. Basic work in this area was performed by Savage (1954), and projections based upon this technique have been used in engineering (Norton, 1963) and financial (Hertz, 1964; Greer, 1970) analysis for several years.

In attempting to estimate possible outcomes from the operation of yet to be installed equipment, engineers and other technical personnel usually employ both objective and subjective judgement. Objective data may sometimes be obtained from reference materials, equipment suppliers, experimental data from pilot operations, and actual experience from the operation of identical or near-identical equipment under similar conditions. While in a number of cases, adequate background data are available for the development of objective probability estimates, this is not a condition which occurs often enough to prevent a widespread requirement for subjectively derived data. Wherever possible, standard statistical distributions are used for describing such estimates. Often the normal distribution proves adequate, but the more general beta function has received much attention as a basis for the development of time estimates in project management studies (King and Wilson, 1967) and as a basic estimation technique in more general analyses (Kopff, 1970).

The use of standard statistical distributions definitely would simplify certain phases of the evaluation procedure. However, certain aspects of this simplification step may lead to inconsistancies in the analysis. First, the majority of those individuals contributing information on possible outcomes have limited or no knowledge of statistical distributions. Secondly, the true distribution of possible outcomes from a specific operation may not resemble the distribution which is to be used as a modeling aid. The combination of these two factors seemingly could result in the forced fit of the subjective outcomes into a class of fairly similar distributions. The creation of an entire array of unimodal, nearly symetric or symetric distributions can result when actually the judges may have felt that a number of the outcomes should have uniform or even triangular densities.

In an attempt to alleviate or at least minimize some of the possible problems of using standard distributions, a questionnaire employing the development of a nonstandard cumulative density function (CDF) was prepared. Previous work in the area of subjective estimation (Winkler, 1967) indicated that the utilization of questionnaires employing either estimated probability density functions (PDF) or CDFs work comparable with regard to technical results. However, the concept of cumulative probability appeared to be more easily understood by the respondents and thus the amount of time required was reduced. A copy of a representative questionnaire is illustrated in Figure 8. The use of this type of questionnaire provided generally acceptable results.

Conclusion

The nonlinear additive weighting model presented earlier in this paper is refined by input data of a specific nature. In order to provide this data, a multiple step collection procedure has been developed. The six primary steps of this process are as follows: (1) determination of primary attributes, (2) establishment of relative importance weights for these attributes, (3) division of the attributes into subfactors

Primary Attribute ____________ Alternative ____________

Subfactor Name ____________ Information Source ____________

Measurement Units ____________ ____________

1. What do you consider to be the largest possible value that ____________ can have? The largest possible value is defined such that you feel 99 out of 100 plants have that value or less. ______

2. What do you consider to be the smallest possible value that ____________ can have? The smallest possible value is defined such that only one plant out of 100 would have a value smaller. ______

3. Can you determine a value of ____________ ____________ in this range such that there is a 50-50 chance that the "true" value will be above or below this value, i.e. the median? Note this value. ______

4. For the range between the lowest possible value (2) and the median value (3), what value in this range would divide the range into two sections of equal probability, i.e. 25% in each? ______

5. For the range between the median value (3) and the largest possible value (1), what value of the range splits the area into two segments of equal probability? ______

6. For (4) and (5) above, divide each of these smaller ranges into two intervals such that each interval contains equal probabilities. Record the value where this would occur. (Refer to the graph below.)

   a) (2) to (4) Low value to mid-median ______
   b) (4) to (3) Mid-median to median ______
   c) (3) to (5) Median to mid-median of high values ______
   d) (5) to (1) Mid-Median of high values to high values ______

Figure 8. Typical Questionnaire for Development of Expected Alternative Performance Profiles.

for which measurable criteria are available, (4) distribution of primary attribute weights among the component subfactors, (5) development of relative impact-scaling functions for the subfactors, and (6) establishment of estimated performance distributions for each alternative being considered.

While the model being developed is primarily quantitative in nature, attention is devoted to the inclusion of qualitative data. For this reason, the acquisition of subjective judgements in the form of expert opinions is an important part of the data collection process. Care must be exercised in the collection and use of such data, and the contributing participants should be made fully aware of both their role in input data generation and what use will be made of the final results. Several valid techniques are available for systematizing and organizing the collection procedure, but the ultimate reliability of the results is directly dependent upon the quality of the relationship between the analyst and the contributor.

VI. DATA ANALYSIS METHODS

The data collection procedure illustrated in the preceding chapter was developed to gather information in a specific form. It is now necessary to develop a series of analysis techniques which permit the full incorporation of this information into the decision making process. Attention in this chapter is focused towards synthesizing all the information available in a method which will allow direct quantitative comparisons to be made among the available alternatives.

In the selection and development of an evaluative analysis technique, several characteristics are considered important. Desirable properties include:

- The ability to easily incorporate various forms of probabilistic input data
- The capability of utilizing nonlinear utility or scaling functions
- Provisions to allow the analyst an opportunity to experiment with various hypothetical site-design combinations
- Flexibility of output form so as to encourage future model development
- Relative ease of data presentation, computation, and operation
- Capability of allowing sensitivity studies involving all input parameters.

The primary vehicle in the development of the technique embodying these characteristics is the nonlinear additive weighting model. The basic concepts inherent in this model were earlier discussed in Chapter IV.

Simulation of Potential Environmental Impacts

While the arithmetic technique presented in Chapter IV does provide an accurate evaluation of expected impact values, it does not easily permit sensitivity analysis nor does it allow a high degree of adaptability in comparing hypothetical or proposed alternatives. In order to more fully develop the flexibility of the evaluation procedure, two computer based simulation models have been developed.

Both of these models are based on the generation of a series of random numbers which are then used to select specific outcomes from a probability distribution of possible occurrences. In the situation under consideration, these randomly generated values are used to simulate specific alternative performance characteristics. These performance values are then transformed into representative impact estimates through the application of the utility or scaling functions as illustrated earlier in Chapter IV. This stochastic sampling simulation technique, more colorfully called Monte Carlo, has been used in risk simulation for several years (Malcolm, 1958; Hertz, 1964; Dienemann, 1966). A number of well-developed computer codes are available for specific simulation activities, but in this paper the programs were written in the FORTRAN IV language by the author. Programming and computational work was done at the Oregon State University Computer Center, and the uniform random number generating routines were provided by the Center.

The first of the programs will be employed to derive a weighted total value for potential environmental impact (PEI)for each alternative, and will be discussed in this section. The second program will be used for developing a procedure of selecting between multiple activities and will be developed later in this chapter.

The primary function of the first program is the generation of a distribution representing the aggregate PEI of each of the alternatives being considered. This generation is accomplished by a large number of simulations utilizing the data collected earlier. Basically the steps of this procedure are as follows:

1. Generate a single uniform random digit in the range 0.0 to 1.0.
2. Determine the performance level corresponding to this value for the subfactor under consideration.
3. Transform this performance level into a measure of potential impact through the use of the subfactor impact-scaling function.
4. Multiply the simulated impact by the subfactor importance weight.
5. Perform steps one through four for all subfactors being considered and sum the weighted subfactor impacts to obtain a simulated total impact value.
6. Perform steps one through five until a distribution of total weighted impact values is generated for the alternative under consideration.
7. Calculate statistical measures of the alternative PEI and print the results in tabular form.
8. Perform steps one through seven for all alternatives being considered.

A generalized flow chart of the program is shown in Figure 9 and a program listing is provided in Appendix A.

Simulations using this type of program were used to develop a representative total PEI distribution for the site under consideration.

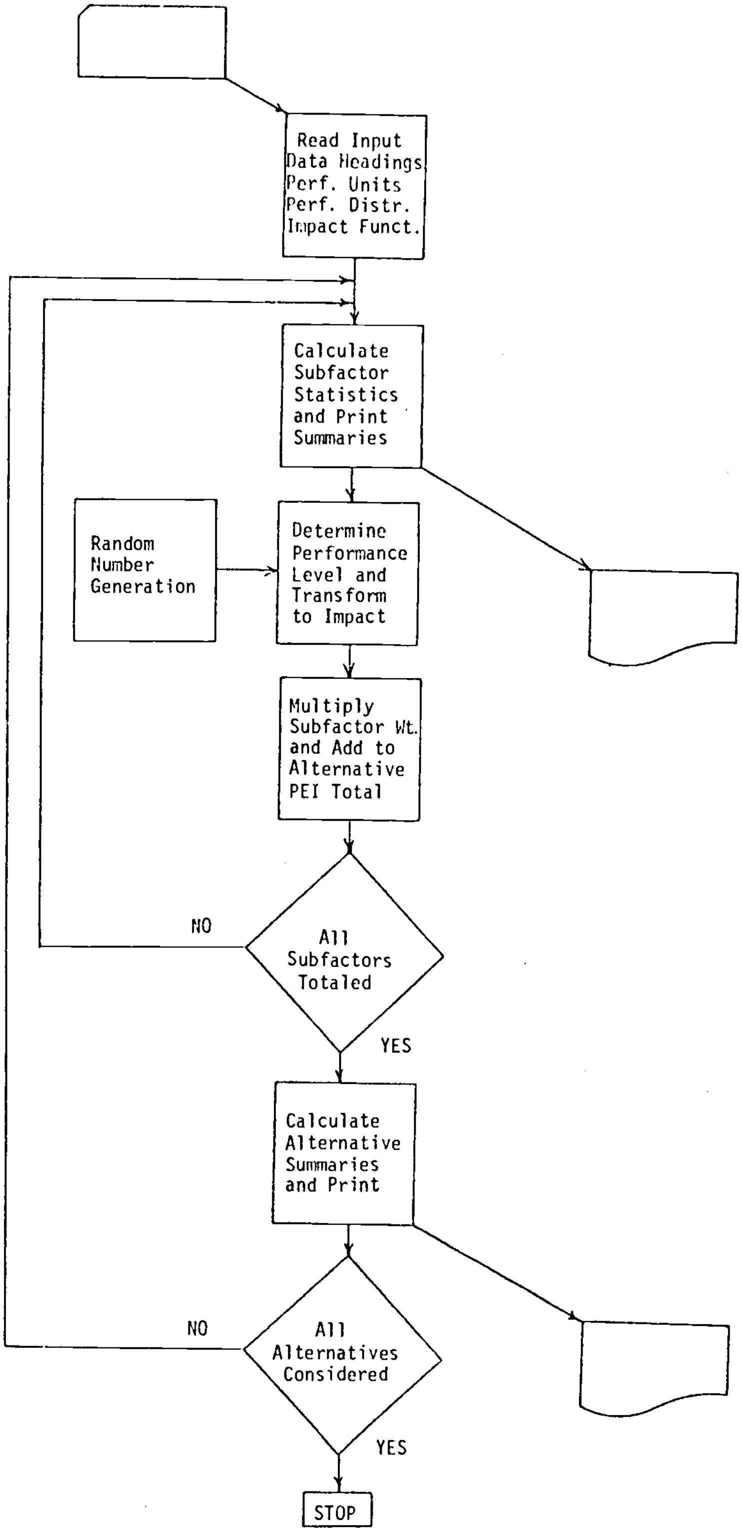


Figure 9. Flow Chart of Simulation Program for Determination of Potential Environmental Impact

Results of these simulations using the original data estimates are shown in Table XII. The mean and variance of this distribution simulated PEI values are 0.38 and 9.43 x 10^{-4} respectively.

Theoretically, the results of the simulation should approximate the normal distribution. As an initial test, these values were first plotted on normal probability paper. When visual inspection of results seemingly indicated a good fit, the Kolmgorov-Smirnov (Ostle, 1963) goodness of fit test was applied. In this case, there is no reason to reject the hypothesis of normally distributed values at the 0.5 level.

Development of a Graphical Comparison Technique

In order to develop an aggregate measure of alternative desirability, it is necessary to consider the combination both of direct costs and nonmonetary effects. The selection of units for the measure of direct costs is left to the analyst. Cost may be expressed in myriad ways, but the most common are in dollars per unit of output or equivalent uniform annual cost (EUAC). Development of an estimated equivalent annual cost utilizing the factors discussed in Chapter II results in an annual coded value of $14.1 x 10^7 per year. Data of this type would then be collected on all site-design alternatives which are to be considered in the final phases of the evaluation. An array of such data which includes the previously developed values as alternative A, and a series of hypothetical entries for comparative purposes is shown in Table XIII.

TABLE XII. RESULTS FROM SIMULATION OF POTENTIAL ENVIRONMENTAL IMPACT

IMPACT	RELATIVE PROBABILITY	CUMULATIVE PROBABILITY
0.310	0.00	0.00
0.320	0.02	0.02
0.330	0.03	0.05
0.340	0.04	0.09
0.350	0.05	0.14
0.360	0.09	0.23
0.370	0.11	0.34
0.380	0.17	0.51
0.390	0.15	0.66
0.400	0.13	0.79
0.410	0.11	0.90
0.420	0.06	0.96
0.430	0.03	0.99
0.440	0.01	1.00
0.450	0.00	1.00

TABLE XIII. HYPOTHETICAL DATA FOR COMPARISON OF ALTERNATIVES

Site-Design Alternative	Expected EUAC $ x 10^7	Expected PEI
A	14.1	0.38
B	15.3	0.49
C	9.8	0.82
D	10.0	0.68
E	17.0	0.33
F	22.1	0.32
G	11.2	0.52
H	12.4	0.48
I	13.3	0.61
J	13.0	0.73

These values could represent ten separate locations within a region of interest or they could describe the costs and effects of ten different design alternatives at a single site. Most likely there would be a combination of these conditions with say three basic designs being considered at four or five potential sites. Since the direct cost components are stated in terms of dollars per year, it is essential that all the alternatives being considered provide an equivalent level of service.

If one of the available alternatives had both the lowest EUAC and the minimal expected environmental impact, it would obviously dominate all other members of the set. Unfortunately, this situation rarely occurs in actual practice; either in choices between sites, or in the comparison of alternative pollution control proposals at a single location. In addition, even if an alternative did appear dominative at this point, no consideration of variation in outcomes or risk has been introduced. For these reasons, it will be necessary to extend the analysis into areas where the selection of one alternative over another includes various compromises or trade-offs.

With the data now available, it is possible to graphically illustrate the realtive desirability of the alternatives being evaluated. A display of the alternatives and their relationship to each other is provided in Figure 10. This chart permits a rapid basic overview of the choices being considered and in some instances will allow a reduction in the number of candidates.

In the situation currently under examination it is evident that the alternatives along the line FEAGDC potentially dominate the other possible choices. That is, it appears that regardless of the relative importance being placed on direct versus indirect costs, the optimum selection must lie along the line F→C. This situation is analogous to the concept of a feasible solution space in linear programming problems. The alternatives represent a collection of feasible solutions which constitute a convex set. In this case, the alternatives are to be compared on the basis of some weighted combination of direct and indirect values. Since a minimum weighted value will be considered as most desirable, the process of selection is not unlike the standard formulation of a minimization problem. Therefore, if the situation under study contained only exact non probabilistic data, the optimum solution must lie at one or more of the set of extreme points {F E A G D C}. The only difficulty being in the development of an acceptable objective function. The function in this analogy represents the relative importance of EUAC and environmental impact.

Other factors may also be represented on the chart. It is possible that capital constraints would eliminate certain of the potential alternatives. If a maximum EUAC of \$20 s 10^7 was set, then alternative F would be eliminated from further consideration. Likewise, a policy of

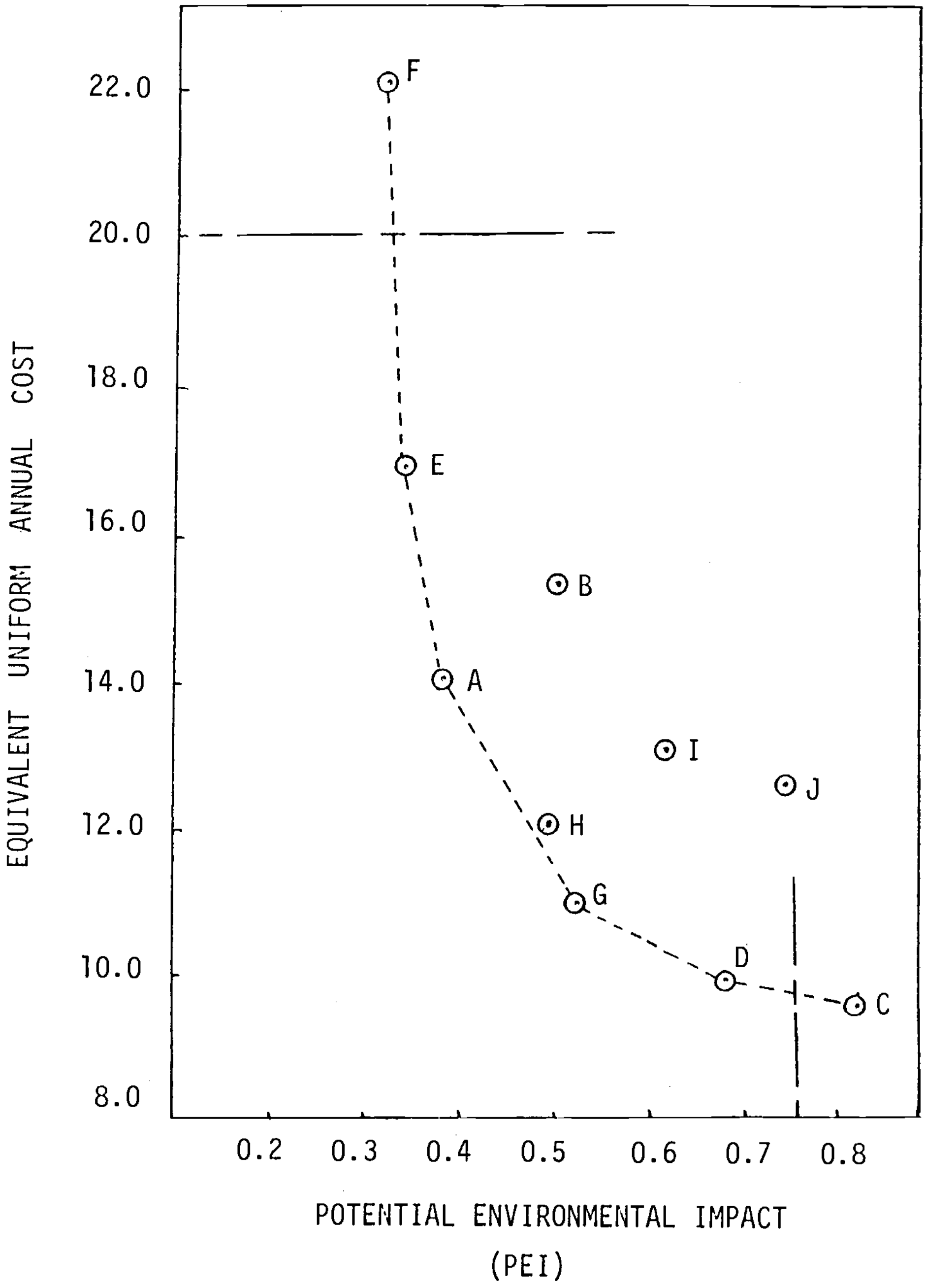


Figure 10. Relative Desirability of Alternatives

not considering any alternatives with severe PEI, say above 0.75, could be adapted. Under such conditions, the feasible alternative set would be reduced to {E A G D}. However, since variances do exist in the input data, it may be desirable to include such alternatives as H in the analysis procedure. The possibility will be illustrated later in the chapter.

Development of a Linear Comparison Model

The problem of developing an acceptable objective function through some type of weighted combination of direct and indirect parameters remains critical. While a deterministic answer is not yet available, it is possible to illustrate the effect of various component weighting ratios on the alternative selection procedure. This step will thus be a form of sensitivity analysis.

In attempting to develop some form of aggregate alternative index, it is evident that a problem of units exists. The EUAC is expressed in dollars while the PEI has been purposely derived as a dimensionless quantity. This solution produced no difficulty in the graphic approach started in Figure 10, but it must be resolved prior to developing a single comparable numeric value to represent each alternative.

The candidate field currently being considered is represented by the following values:

Alternative	E	A	G	D
EUAC ($\$10^7$)	17.0	14.1	11.2	10.0
PEI	0.33	0.38	0.52	0.68

The relative or normalized standing for each alternative in terms of EUAC comparison to the others is obtained by taking the most preferred (smallest) number as a base and determining the proportional values of the alternatives to this base. Alternative D with an annual cost of \$10.0 x 10^7 is the minimum of this collection. If a base of 100 is to be assigned to this minimum, then the relative standardized value of alternative G would be $\frac{11.2}{10.0} \times 100 = 112$.

A standardized total PEI for these alternatives can be determined by using essentially the same procedure. In the reduced array of available alternatives, alternative E with a value of 0.33 would be used as a benchmark. Results of the standardization procedure where smaller numbers show a preference are shown below:

Alternative	E	A	G	D
Standardized EUAC	170	141	112	100
Standardized PEI	100	115	157	206

It is now suggested that an overall aggregate index can be calculated as follows:

$$\begin{array}{c}\text{Overall}\\ \text{Aggregate}\\ \text{Index}\end{array} = \begin{array}{c}\text{Standardized}\\ \text{EUAC}\end{array} + \left[R \times \begin{array}{c}\text{Standardized}\\ \text{PEI}\end{array}\right]$$

where R is a dimensionless unit obtained forming the ratio of standardized PEI to standardized EUAC. For example, if environmental and socioeconomic effects are determined to be of relatively small importance compared to total annual costs of owning and operating the facility, R would be very small. If environmental considerations and total annual costs are assumed to be or nearly equal importance, then the value of R would be near 1.0. For projects where environmental concerns are of primary importance, R could then be much greater than 1.0.

Given a range of R values that might be regarded as feasible for alternatives being investigated, it is now possible to develop a graphic display of the overall aggregate index (OAI) for the alternatives under consideration.

	ALTERNATIVE			
	E	A	G	D
R = 0.0, OAI =	170	141	112	100
R = 1.0, OAI =	270	256	269	306

The OAI values shown were calculated using the expression provided above. Since OAI varies linearly with R, only two points in each alternative are required for the completion of Figure 11.

As would be expected from the previous discussion of the similarities between this situation and the basic linear programming problem, each of the basic feasible solutions (alternatives) provides an optimum choice of some objective function. Due to the linearity of the various OAI functions, the cross-over points between alternatives can be calculated easily. For instance, r, the point of equal desirability between alternatives D and G is determined as follows:

$$\begin{aligned} \overbrace{100 + 206R}^{\text{Alternative D}} &= \overbrace{112 + 157R}^{\text{Alternative G}} \\ R &= 12/49 \\ \therefore\ r_1 &= 0.244 \end{aligned}$$

The other points of sensitivity can be determined as $r_2 = 0.689$ and $r_3 = 1.933$.

In addition, a comparative relationship between the information presented in Figure 10 and Figure 11 can be shown using the concept of a benefit to cost (B/C) ratio. For example, if alternative A is compared to alternative G, the following relationship is observed in Figure 11.

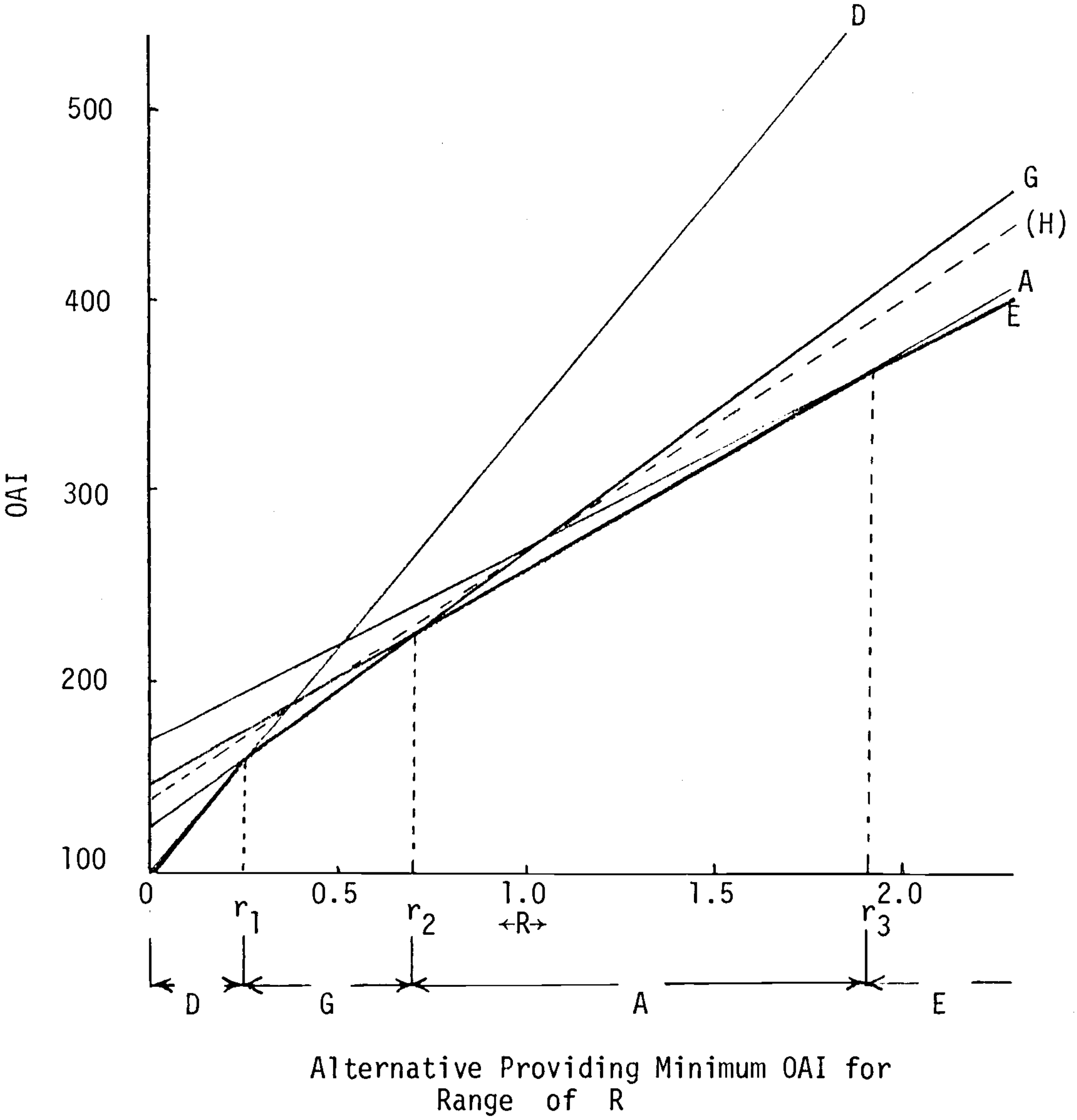
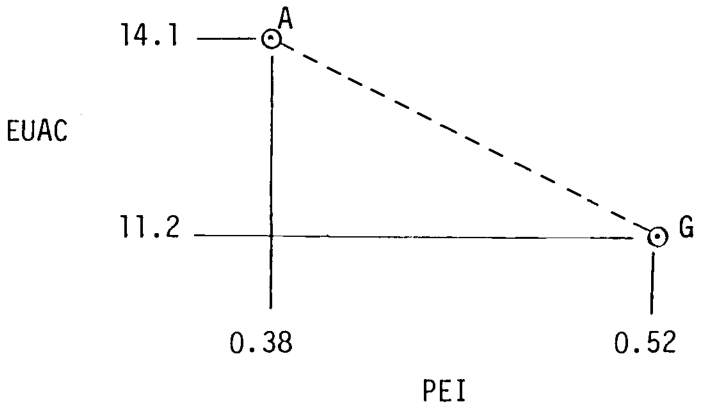
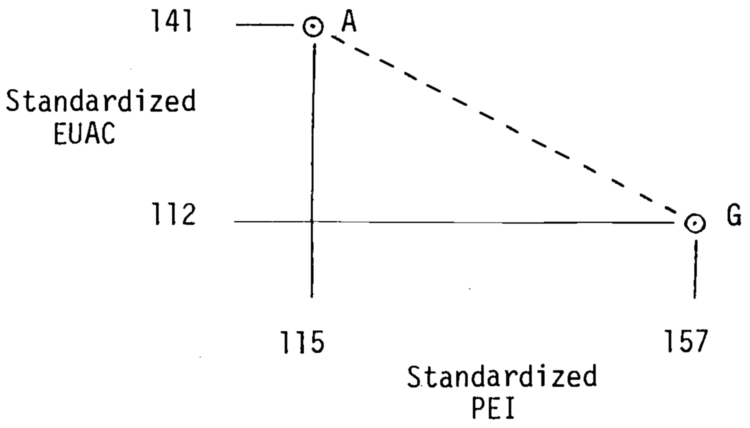


Figure 11. Relationship of Overall Aggregate Index (OAI) to Various Values of R.



This data implies that in order to decrease the potential environmental impact (a decrease in a disbenefit is thus a benefit), it will be necessary to increase the expenditure required. However, it is impossible to develop a meaningful B/C ratio due to the dissimilarity of the measurement units.

This situation can be remedied by the replacement of raw data by the standardized values obtained previously. The new graphic relationship of alternatives A and G is shown below.



The benefit in reduced environmental impact of selecting A over G is therefore 157 - 115 = 42 dimensionless units and the cost of doing so is 141 - 112 = 29 dimensionless units. The benefit to cost ratio would then be calculated as B/C = 42/29 = 1.45. However, it must be remembered that this ratio holds only if the standardized units of benefit and cost have equal weight. In other words, when the previously described value of R is equal to 1.0.

To determine the value of R at the point of indifference between alternatives the following relationship is solved: B/C = 42R/29 = 1.0. Thus the value or R = 42/29 = 0.689 is obtained. This result is the same as that obtained earlier from the analysis of Figure 11. The implication is simply that if environmental concerns are only about 0.7 as important as direct costs, then alternatives A and G are equally attractive. Therefore, for R values in excess of 0.7 the benefit-cost ratio on the additional expenditure required for alternative A over alternative G exceeds 1.0 and for R values lower than 0.7 this ratio is less than 1.0.

In addition, alternative H with standardized EUAC and PEI values of 124 and 145 is shown also in Figure 11 as a dotted line. This is to illustrate again the relationship between the information contained in both figures. Alternative H is shown on the earlier chart as being just inside the convex feasible solution space, thus it was said to be dominated by the alternatives listed in the reduced basic feasible solution set {E A G D}. Although it is barely dominated, it cannot be considered as a potential optimum solution if only deterministic values of EUAC and PEI are to be considered. This same condition can also be noted in the second of the two figures. The line showing the OAI value of alternative H with respect to R is never a part of the minimum OAI boundary, and thus it can be seen that this alternative is dominated by those which contribute line segements to the boundary.

From this illustration it is evident that:

- For low values of $R < 0.244$, alternative D appears to be preferred due to a low uniform equivalent annual cost.
- For high values of $R > 1.94$, alternative E appears to be preferred due to a relatively low environmental impact.
- Alternatives G and A appear to be the preferred alternatives over the mid-range values of R with selection between them possibly sensitive to other factors.
- By using only expected values in this analysis, alternative H appears to be dominated, although for values of R over the range $0.4 < R < 1.0$ alternative H is close to the preferred option.
- The effects of probabilistic EUAC and PEI values have not been taken into account.

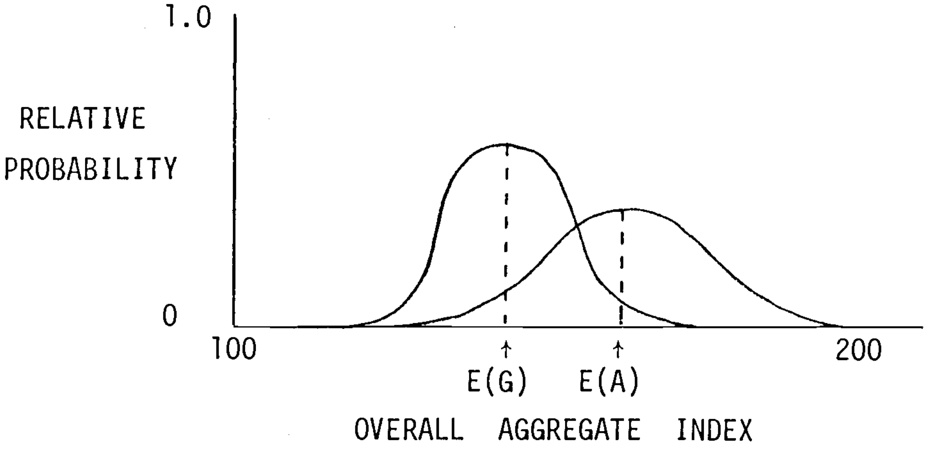
Incorporation of Variability

In order to further analyze the sensitivity of the alternative selection procedure to variability in the aggregate measures, it will be necessary to incorporate probabilistic information into the analysis. Additional data concerning the variability of the four basic, and one nearly basic, alternatives are given in Table XIV.

TABLE XIV. ADDITIONAL DATA FOR COMPARISON OF ALTERNATIVES

Site-Design Alternative	Expected PEI	Variance of PEI	Expected EUAC	Variance of EUAC
A	0.38	9.34×10^{-4}	14.1	3.75
D	0.68	7.20×10^{-4}	10.0	1.55
E	0.33	3.98×10^{-4}	17.0	3.70
G	0.52	3.48×10^{-4}	11.2	1.05
H	0.48	4.14×10^{-4}	12.4	1.09

With this information, it is possible to compute for any given value of R, the incremental difference in OAI between each pair of alternatives. When only two alternatives are being considered, this situation can take the general form shown below.



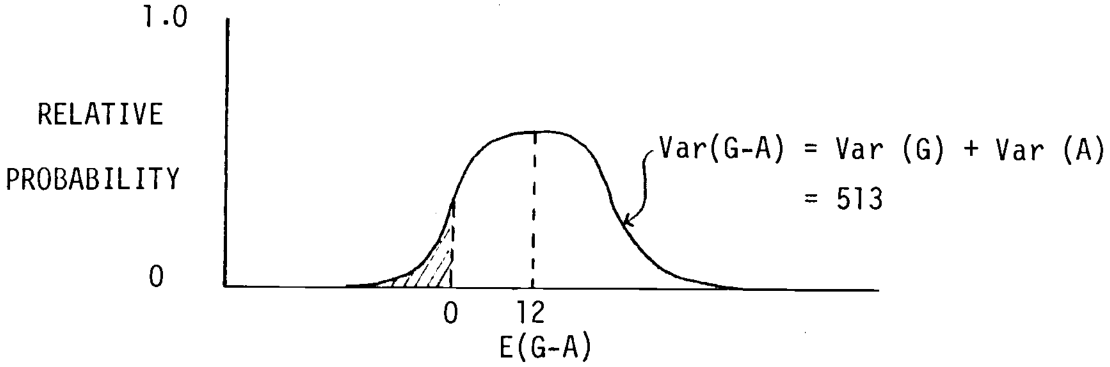
Where the expected total OAI for alternative G is less (therefore more preferred) than that of A. However, due to the variability present, there exists a possiblity that under certain conditions the value of A could be less than G. Obviously, if the probability density functions do not overlap, one alternative would always dominate the other.

Under most conditions and using either discrete or standard continuous density functions, the value of the difference in OAI and the variance of this difference can be routinely calculated for a specific value of R. If the two measures are assumed to be normally distributed, not always a safe assumption, the difference between their means will take the form of a normal distribution with the expected difference, E(d), equal to E(A) - E(G), and its variance, Var(d), will equal Var(A) + Var(G).

This type of analysis can readily be shown for any specific value of R, if the assumptions concerning normality are permitted. As an example, using a value of R equal to 0.4, the mean and variable of the expected OAI values for alternative G can be calculated as follows:

$$\begin{aligned} E(G) &= \text{Standardized EUAC} + (R \times \text{Standardized PEI}) \\ &= 112 + (0.4 \times 157) \\ &= 175 \\ Var(G) &= Var\ (\text{Standardized EUAC}) + (0.4)^2\ [Var(\text{Standardized PEI})] \\ &= 105 + (0.16)\ (31.97) \\ &= 110 \end{aligned}$$

Similar calculations for alternative A result in an expected OAI of 187 with a variance of 403. Therefore E(d) equals 187 - 175 or 13 and Var(d) = 110 + 403 or 513. This result can be illustrated in graphic form as shown below.



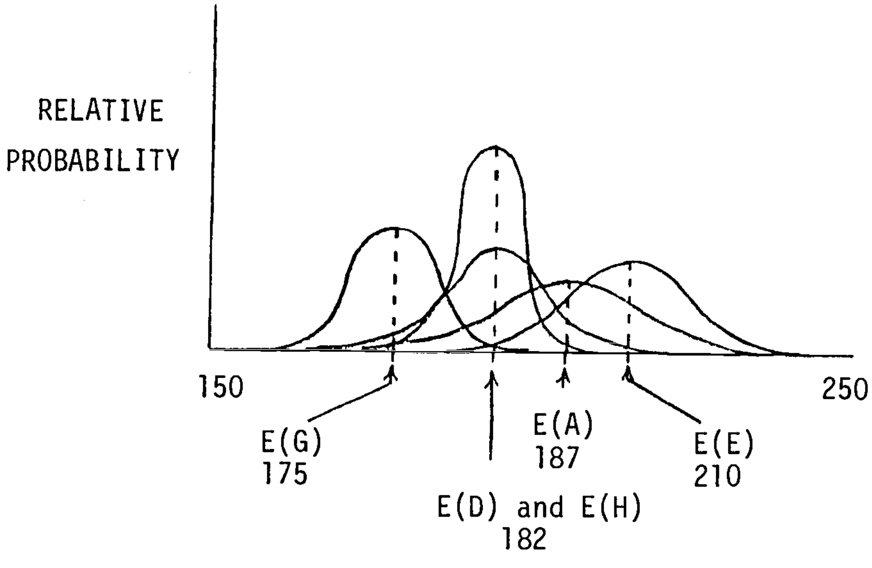
The shaded area at the left end of the curve represents the probability of obtaining an OAI value for A less than G during routine operations. Again, with the conditions that alternative A and G are independent and their OAI values are normally distributed, this probability can be calculated.

Probability of randomly obtaining an OAI value of A less than that of G $= Ƶ \; \frac{0 - 12}{513}$

$$= Ƶ\,(-0.53)$$

$$\doteq 0.30$$

In cases where multiple alternatives are being considered, the comparison problem becomes more complex. For example, if the OAI values for the five comparative alternatives are observed at a value of R equal 0.4, the situation would appear graphically as follows:



OVERALL AGGREGATE INDEX
(Not to Scale)

This hypothetically contrived situation illustrates the complications involved in performing the type of analysis employed when only two alternatives were being considered. The situation is made more complex if the assumptions concerning the use of normally distributed OAI values are invalid and irregular density functions must be employed. Additionally, the sensitivity of the relative attractiveness of each alternative to changes in various elements comprising the OAI is difficult to estimate.

Another condition which must be considered is the fact that an explicit value of R is difficult to obtain. This is particularly true during the early stages of the evaluation procedure. The sensitivity of the alternative procedure. The sensitivity of alternative preference to a range of possible R values could possibly be a critical factor depending upon the relative importance placed on environmental effects by evaluation and review groups.

Development of an R-Sensitive Simulation Model

The final step in the data analysis procedure is the development of a simulation model which permits the incorporation of all the data thus far obtained. This program provides for the inclusion of various discrete or piecewise continuous input data distributions, and allows the evaluation of a number of alternative situations within a relatively short period of time.

The primary function of this program is the generation of a series of probabilities showing the proportion of time each alternative provides a minimum OAI value under varying conditions. In addition, it provides the analyst with a complete range of statistical information on input data, standardizes this data and provides the parameters necessary for the construction of the displays shown previously in

Figures 10 and 11, and produces a complete statistical summary of OAI values for any range of R values the analyst chooses. Basically the operational steps of the program are as follows:

1. Read input information for each alternative under consideration.
    a. Alternative name
    b. PEI values and Probabilities
    c. EUAC values and probabilities
2. Determine and print statistical parameter of PEI and EUAC for each alternative.
3. Select basic values and develop standardized distributions for each alternative.
4. Determine OAI values at R = 1.0 and print with summary of data from step three.
5. Generate two uniform random digits in the range 0.0 to 1.0 and determine corresponding standardized PEI and EUAC values for the alternative under consideration.
6. Calculate the appropriate OAI value for the R value of interest.
7. Perform steps five and six for each alternative, and select the alternative which has the minimum OAI.
8. Perform steps five through seven until a relative frequency distribution of outcomes for each alternative is generated.
9. Calculate statistical parameters of OAI for each alternative for specified R values and print with a summary of results from step eight.
10. Perform steps five through nine for all R values under consideration.

A generalized flow chart of the program is shown in Figure 12, and a

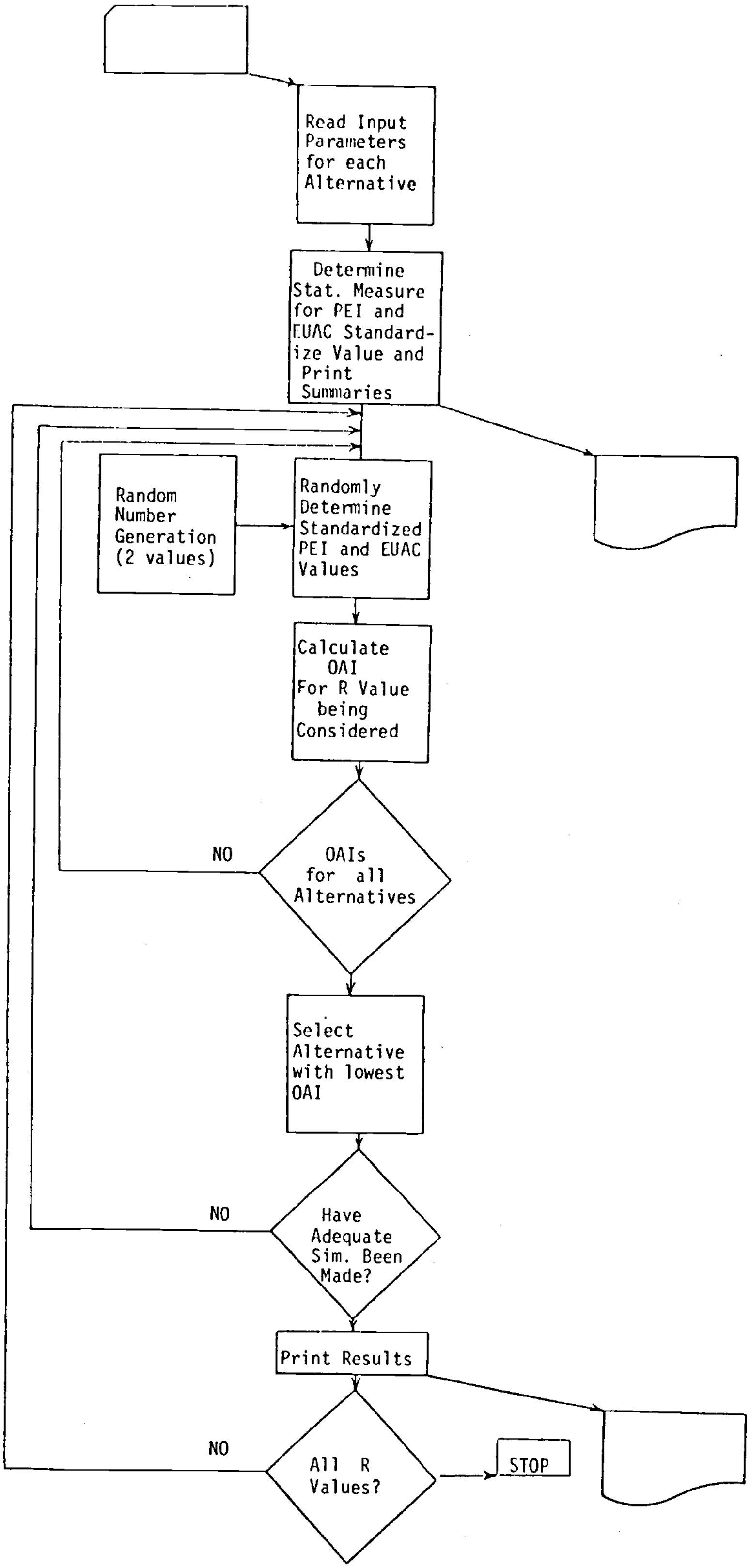


Figure 12. Flow Chart for OAI Simulation Program

complete program listing and user guide is provided in Appendix B.

Returning to the previous alternative comparison problem for an R value of 0.4, it is now possible to obtain the results shown in Table XV. It should be noted that the values for the means and variances of Alternative A and G are very close to those obtained analytically.

TABLE XV. RESULTS OF SIMULATED OAI FOR FIVE ALTERNATIVES AT R = 0.4, N = 1000.

Alternative	Average Simulated OAI	OAI Variance	Minimum OAI Occurrences	Relative Frequency
A	187.1	414	224	0.224
D	182.3	164	208	0.208
E	209.3	373	8	0.008
G	174.5	115	401	0.401
H	181.9	118	159	0.159

However, the flexibility of the simulation model also permits a rapid evaluation of the alternative preference patterns for any range of R values. The results of a series of simulations for R values from 0.0 to 2.0, inclusive, are shown in Table XVI. This information is probably more acceptable for quick visual assimilation when presented in graphic form. A graphic illustration of the simulation results is provided in Figure 13.

Discussion of Results

The primary factor which should be remembered at this point, is that this simulation was performed using a significant amoung of hypothetical data in conjunction with that which was empirically obtained. Thus the conclusions which may be drawn from the simulation output are made for discussive purposes only.

TABLE XVI. RESULTS OF FIVE ALTERNATIVE SIMULATIONS FOR 0.0 ≤ R ≤ 2.0, N = 500 CYCLES

R= ALT	0.0	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
A	0.023	0.084	0.234	0.356	0.486	0.538	0.534	0.528	0.512	0.490	0.438
D	0.771	0.448	0.200	0.052	0.010	0.000	0.000	0.000	0.000	0.000	0.000
E	0.000	0.000	0.010	0.058	0.142	0.234	0.340	0.384	0.434	0.478	0.548
G	0.182	0.364	0.402	0.328	0.218	0.112	0.060	0.032	0.006	0.006	0.000
H	0.024	0.104	0.154	0.206	0.144	0.116	0.066	0.056	0.048	0.026	0.014

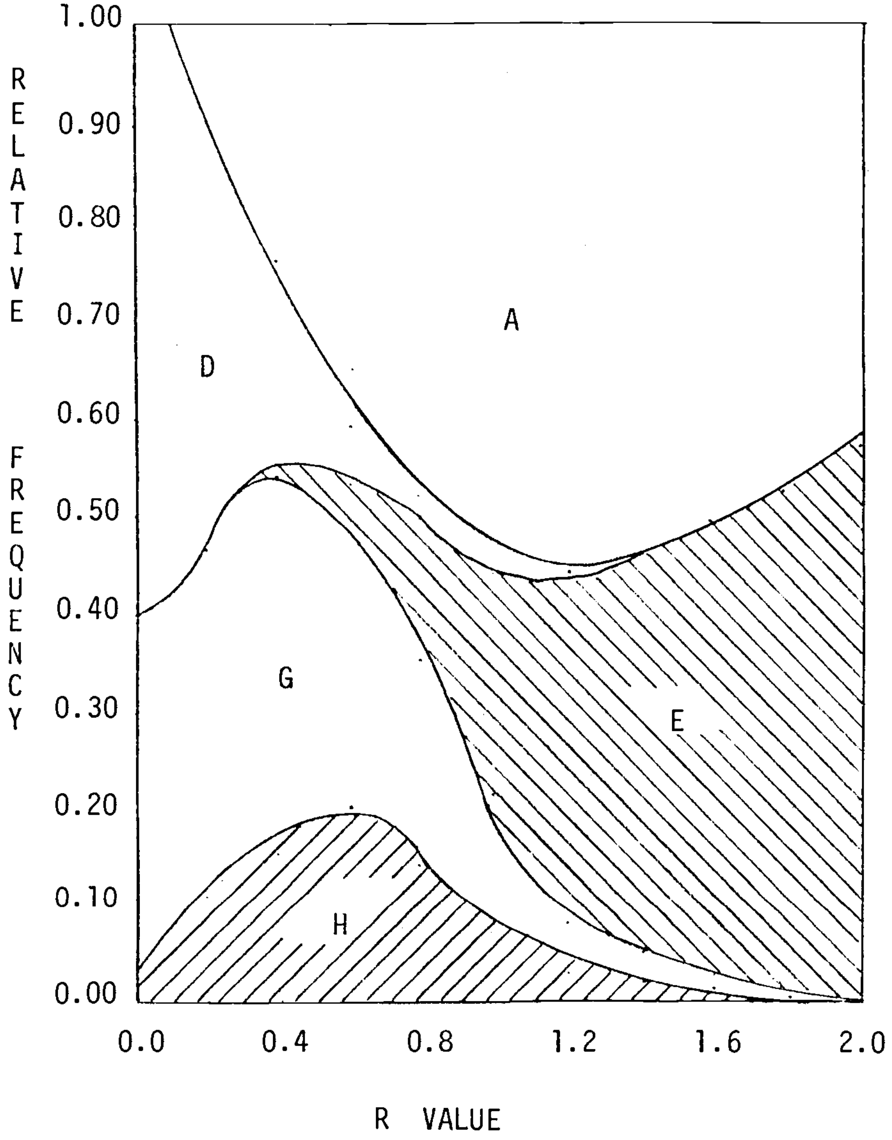


Figure 13. Graphic Display of Simulation Results for $0.0 \leq R \leq 2.0$.

Observations of the data presented in Table XVI reveals the following points:

- For very low R values, or when EUAC is to be the only consideration, alternative D is an overwhelming choice due to a low annual cost.
- For very high R values, alternative E appears to be preferred, but alternative A is still quite strong for R values as high as 2.0.
- Alternatives G and A appear to be preferred over the mid-range values, $0.4 \leq R \leq 0.8$, with G appearing stronger at the lower end of the range and A at the upper end.
- Alternative H, although never a basic selection of the deterministic model, has the minimum OAI as high as 20 percent of the time for certain mid-range values.

Perhaps the most interesting points of this display pertain to the variances of the alternatives. The expected OAI of alternative A has a rather large variance, thus this alternative appears to be preferred over a large range of R values. In actuality, the amount of risk associated with a large variance alternative is quite high, as very large, as well as very small values can result. If this alternative happens to be among the final choices in the evaluation procedure, then additional simulations can be made over the range of R values which have been selected as critical. For example, if R values between 1.0 and 1.6 are of interest, the alternatives A and E can be compared independently of the other alternatives. Based on a sample of 1000 simulations the following results were obtained.

R VALUE

ALT	1.0	1.2	1.4	1.6	1.8	2.0
A	0.602	0.499	0.489	0.402	0.361	0.315
E	0.398	0.501	0.511	0.489	0.639	0.685

(Relative Frequencies)

It must be remembered that these results were obtained from the comparison of alternatives A and E independently of the other candidates. Thus, a change in the base used for the standardization of PEI and EUAC values will probably result. The only time this will not occur is when two of the alternatives being compared independently represent the extreme minimum points of PEI and EUAC for the original data set. However, this condition does not cause any difficulty as generally the other candidates have been dropped from contention, and therefore new comparative parameters should be determined anyway. Regardless of the number of alternatives being considered, the ratio of PEI to EUAC for each alterantive depends upon the R value being employed, thus the simulation procedure remains valid.

Observation of the data presented in Figure 13 also reveals the presence of alternative H as a candidate alternative. The magnitude of this alternative's relative frequency as a minimum OAI choice is directly dependent upon the variability in its OAI value. Obviously, if the OAI values have negligible dispersion, the relative frequency would decrease with near proportionality. Other factors affecting any near-basic alternative's relative frequency patterns would include the variability of candidates with similar aggregate parameters and the relative proximity of the alternative to the boundary of the basic solution area represented earlier in Figure 10.

CONCLUSION

The techniques and procedures developed and presented in this chapter represent the final steps in a multi-phase evaluation procedure. They are designed primarily for the generation of information in such a form as to facilitate the comparison of alternatives represented by arrays of data based upon both quantitative and qualitative factors.

Through the application of these methods, the inital collection of candidate alternatives may be compared and possibly reduced in number. Successive steps of the procedure allow the introduction of descriptive probability density functions and permit the development of an aggregate measure of alternative desirability. Simulation based modeling procedures are employed to encourage the use of sensitivity studies and allow the easy introduction of data representing hypothetical or proposed alternatives.

VII. CONCLUSIONS AND RECOMMENDATIONS

The objective of this dissertation was to present the formulation of a systematic approach for the comparative evaluation of site-design alternatives. Numerous methods have been developed for the analysis of facility location problems, but most of this work involves the treatment of direct cost inputs in deterministic form. However, factors involving environmental or other nonmonetary elements are becoming more important in the decision process. This consideration is particularly true in large scale projects where construction and operation activities result in significant disruption of existing environmental systems.

Therefore, the primary focus of the work presented in this paper was an attempt to develop an evaluation procedure which both allows the inclusion of qualitative information and provides the capability for analyzing probabilistic data. Additional emphasis was given to the difficulties involved in the conversion of engineering estimates of physical performance into the probable environmental changes resulting from the systems being considered. Finally, a method for the determination of an overall aggregate measure of attractiveness for each alternative and a technique for observing the sensitivity of this measure were developed.

Characteristics of Present Methodology

The procedural methodology presented in this paper is based primarily on rather lengthy extensions of the well known linear weighting model. Whereas the basic model was developed primarily for the deterministic evaluation of multiple alternatives, these extensions include provisions for the incorporation of probability density functions as both input and output forms. Additionally, the methodology permits the use of subjective data in the form of expert opinions as a device for the transformation of qualitative data into quantitative measurement units. A further extension of this transformation technique eliminates the requirement for a single person or group to determine both expected facility performance and the effect of this performance on the environment.

In order to obtain this separation of cause and effect data, probabilistic alternative performance predictions are obtained from design and operating personnel, and are then transformed into potential impact estimates through impact-scaling functions. These functions, which may be nonlinear, are developed independently from the design factors concerning any individual alternative. Thus, even though multiple site-design alternatives may be considered, the scaling and weighting elements of the evaluation procedure are performed so as to provide a uniform nonbiased series of comparable values. The aggregate value obtained for each alternative is then developed as a probability density function through the application of a simulation model.

These probabilistic elements of potential environmental impact (PEI) are then combined with the aggregate direct cost estimates in the form of uniform equivalent annual costs (EUAC) to determine a weighted overall aggregate index (OAI). Alternative selection studies are then carried out using values of OAI, weighted by the importance of environmental factors, as a basis of comparison.

The additional flexibility and output detail provided through the use of this procedure is obtained only at the cost of extensive data collection. In comparison with the basic additive weighting model, the methodology employed requires several times as much input information in varying forms. In addition, the determination of representative attribute importance weights and the determination of accurate impact-scaling functions requires the input of numerous knowledgeable judges. An initial observation may result in the opinion that this latter fact represents a disadvantage of the procedure. However, in reality the opposite is true. Most other additive weighting models require fewer subjective estimates, but each of these estimates usually requires an opinion of both alternative performance and the relative impact resulting from this performance. Elimination of this requirement for dual opinions from a single source reduces the need for personnel knowledgeable in both areas and allows the employment of specialists in each aspect of the situation. Additionally, the overall effect of bias on the part of a single judge is minimized significantly.

The conclusion implied here then is that past efforts in the area of site location studies were weak in their lack of consideration of nonmonetary or environmental effects, and usually were not developed so as to permit the inclusion of probabilistic input data. An effort has been made to eliminate, or at least minimize some of these factors. However, the methodology presented requires larger quantities of significantly more detailed input data. In situations where large scale activities involving significant expenditures of capital and potentially high environmental disruption are likely to result, it is thought that the additional costs of the current methodology are outweighed by the benefits obtained from its use. These conditions are nowhere more evident than in the determination of potential nuclear power plant locations. The extreme controversy surrounding such activity makes a sensitive, accurate model a necessity, with the advantages gained in the improved deliniation of alternatives well worth the cost of additional refinement.

Recommended Future Research

The formulation of the evaluation procedure has involved several areas which should prove of interest for future research.

The first of these areas is not one strictly of research, but rather of determining the adaptability of the procedures to industrial plant siting problems. It is thought that the methodology is directly applicable to this area with only minor modifications. The only portion of the overall process which may require developmental effort is in the determination of primary attribute importance weights. Usually, corporate decisions are made by rather small groups, and the Dunn-Rankin technique frequently requires a relatively large sample size. Overcoming this difficulty would require further investigation into possible alternative weighting methods. Primary areas of concentration could include extensions of Torgerson's (1969) constant-sum, paired comparison technique or the feasibility of utilizing a group decision method such as the Delphi technique.

Another area of interest which is directly related to the previous discussion, is the determination of how sensitive the aggregate values are to variability within the attribute importance weights. Dunn-Rankin and King (1969) present a method for determining the average variance of the weights obtained through the simplified rank scaling procedure, but not of the individual values. Even if the variance of the individual weights is determined, the problem of sensitivity remains. Direct Monte Carlo simulation methods are somewhat more involved in this case

(Litchfield and Hansen, 1975) as the process would require the development of marginal and joint distributions.

All of the situations mentioned above involve cases where the primary attributes are assumed to be independent random variables. This assumption is not unrealistic in the power plant siting data employed as an example. However, if the methodology presented was extended into the analysis of certain services such as social welfare or health care, strong interdependencies between attribute values may result. This situation could only be approached after the identification of those significant covariances is completed, and then any attempt at establishing a composite or aggregate indicator through the use of simulation, would require a much more complex model than described herein. The use of utility or scaling functions would seemingly lend itself to the social value type problem, so this area of study may prove beneficial if certain simplifying assumptions can be identified.

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APPENDICES

APPENDIX A

FORTRAN Listing and Data Specifications for PEI Simulation Program

Program PEISIM has been developed to generate desnity functions of potential environmental impact (PEI) values using Monte Carlo simulation. The program employs discrete simulation techniques and utilizes piecewise linear approximations of impact-scaling functions and probabilistic performance estimates. Alternatives described by a maximum of twenty primary attributes, each containing up to ten subfactors, can be accommodated using current specifications.

INPUT DATA FORMS FOR PROGRAM PEISIM

Card Type	Field Description	Format
1	Alternative Name (ALTN) -Maximum of 40 alphanumeric characters	20A2
	Number of primary attributes (NPAT) -Maximum of 20 per alternative	I5
	Input detail code (KODE) -Right adjusted in field. '1' indicates input list desired, '0' indicates no list.	I5
	Number of simulation cycles (NSIM) -Maximum 9999 per un	I5
2	Primary attribute name (PAT) -Maximum of 40 alphanumeric characters	20A2
	Number of subfactors (NSUM) -Maximum of 10 per primary attribute	I2
3	Subfactor name (SUBF) -Maximum of 40 alphanumeric characters	20A2
	Number of intervals in subfactor functions (NUNT) -Maximum of 10 per subfactor	I5
	Relative importance weight (WT)	F5.3
4	Upper bound of measurement units (UNIT)	10F5.0
5	Impact scaling values (SCAL)	10F5.3
6	Probabilistic performance estimates (PERF)	10F5.3

Each primary attribute requires a type 2 card and each subfactor within the attribute requires cards of types 3 through 6.

```
OS3 FORTRAN  VERSION 3.13            08/17/76  0857

      PROGRAM PEISIM
C
C     THIS PROGRAM IS CURRENTLY DIMENSIONED TO PERMIT
C     THE SIMULATION OF TOTAL PEI FOR ALTERNATIVES HAVING
C     A MAXIMUM OF TWENTY PRIMARY ATTRIBUTES WITH UP TO
C     TEN SUBFACTORS FOR EACH ATTRIBUTE.
C
C     VARIABLE NAMES
C     ALTN - ALTERNATIVE NAME
C     AVGP - AVERAGE OF SIMULATED PEI
C     KODE - CODE FOR OPTIONAL PRINT OF INPUT DATA
C     NPAT - NUMBER OF PRIMARY ATTRIBUTES
C     NSIM - NUMBER OF SIMULATION CYCLES DESIRED
C     NUNT - NUMBER OF MEASUREMENT CLASSES PER SUBFACTOR
C     PEI  - POTENTIAL ENVIRONMENTAL IMPACT
C     PERF - PROBABILISTIC PERFORMANCE ESTIMATES
C     SCAL - IMPACT SCALING FUNCTION
C     SUBF - SUBFACTOR NAME
C     UNIT - UNITS OF SUBFACTOR MEASUREMENT
C     VAR  - VARIANCE OF SIMULATED PEI DISTRIBUTION
C     WT   - SUBFACTOR IMPORTANCE WEIGHT
C
      DIMENSION ALTN(20),PAT(20,20),UNIT(20,10,10)
      DIMENSION SCAL(20,10,10),PERF(20,10,10),NSUB(20)
      DIMENSION NUNT(20,10),TALY(100),ITCT(100),WT(20,10)
      DIMENSION SUBF(20,10,20)
C
C     THESE VALUES ARE USED FOR INITIALIZATION OF THE
C     RANDOM NUMBER GENERATOR
C
      IA=4117
      IC=1772721
      IR=205205
C
C
      READ(40,900)(ALTN(NA),NA=1,20),NPAT,KODE,NSIM
      DO 10 I=1,NPAT
      READ(40,905)(PAT(I,NB),NB=1,20),NSUB(I)
      NX=NSUB(I)
      DO 10 J=1,NX
      READ(40,906)(SUBF(I,J,NC),NC=1,20),NUNT(I,J),WT(I,J)
      NY=NUNT(I,J)
      READ(40,910)(UNIT(I,J,K),K=1,NY)
      READ(40,915)(SCAL(I,J,K),K=1,NY)
      READ(40,915)(PERF(I,J,K),K=1,NY)
   10 CONTINUE
      IF (KODE-1)21,11,21
C
C     STATEMENTS 11 THROUGH 20 ARE REQUIRED FOR OPTIONAL
C     PRINTING OF INPUT DATA LIST.  KODE = 1 ON FIRST DATA
C     CARD WILL INITIATE THIS SEQUENCE.
C
   11 WRITE(61,950)(ALTN(NA),NA=1,20),NPAT
      DO 20 I=1,NPAT
      WRITE(61,955)(PAT(I,NB),NB=1,20)
      NZ=NSUB(I)
      DO 20 J=1,NZ
      WRITE(61,960)(SUBF(I,J,NC),NC=1,20),WT(I,J)
      NR=NUNT(I,J)
      WRITE(61,965)(UNIT(I,J,K),K=1,NR)
      WRITE(61,965)(SCAL(I,J,K),K=1,NR)
      WRITE(61,965)(PERF(I,J,K),K=1,NR)
   20 CONTINUE
      TALY(1)=0.0
      DO 21 ICNT = 2,100
      TALY(ICNT)=TALY(ICNT-1)+0.01
   21 ITCT(ICNT)=0.0
      SUMT=0.0
      SST=0.0
      DO 45 KSIM=1,NSIM
      TOTW=0.0
      DO 40 I=1,NPAT
      NT=NSUB(I)
      DO 40 J=1,NT
C
C     RANDOM NUMBER GENERATOR FOR CDC 3300.  FOR USE ON
C     IBM EQUIPMENT, SUBROUTINE RANDU MAY BE INSERTED AT
C     THIS POINT.
C
      IR=AND(AND(IR*3085,8388607)+IC,8388607)
```

```
OS3 FORTRAN  VERSION 3.13 PEISIM    08/15/76 .1641
      PROB=FLOAT(IR)/8388607.
C
C
      NS=NUNT(I,J)
      DO 30 K=1,NS
      IF(PERF(I,J,K)-PROB)30,31,31
   30 CONTINUE
   31 SUBW=WT(I,J)*SCAL(I,J,K)
   40 TOTW=SUBW+TOTW
      SUMT=SUMT+TOTW
      SST=SST+(TOTW**2)
      DO 44 NCT=1,100
      IF(TOTW-TALY(NCT))45,45,44
   44 CONTINUE
   45 ITCT(NCT)=ITCT(NCT)+1
C
C     CALCULATION OF MEAN AND VARIANCE
C
      AVGP=SUMT/FLOAT(NSIM)
      VAR=((SST/FLOAT(NSIM))-(SUMT/FLOAT(NSIM))**2)
      WRITE(61,975)(ALTN(NA),NA=1,20),NSIM
      WRITE(61,980)AVGP,VAR
      WRITE(61,982)
      DO 50 MA=1,25
      MB=MA+25
      MC=MA+50
      MD=MA+75
   50 WRITE(61,985)TALY(MA),ITCT(MA),TALY(MB),ITCT(MB),
     1TALY(MC),ITCT(MC),TALY(MD),ITCT(MD)
  900 FORMAT(20A2,3I5)
  905 FORMAT(20A2,I1)
  906 FORMAT(20A2,I5,F5.3)
  910 FORMAT(10F5.0)
  915 FORMAT(10F5.3)
  950 FORMAT(≠1≠///≠    ALTERNATIVE NAME - ≠20A2/
     1≠    NUMBER OF PRIMARY ATTRIBUTES - ≠,I2)
  955 FORMAT(//3X,20A2)
  960 FORMAT(/3X,20A2,/3X≠RELATIVE WEIGHT = ≠,F5.3)
  965 FORMAT(10F8.3)
  975 FORMAT(≠1≠//10X,≠ALTERNATIVE - ≠20A2/10X
     1≠SIMULATION RESULTS FOR N = ≠,I4)
  980 FORMAT(/10X,≠MEAN PEI =≠,F5.3,3X,≠VARIANCE =≠,F8.6)
  982 FORMAT(//≠ PEI   FREQ≠5X≠PEI   FREQ≠5X≠PEI   FREQ≠
     15X≠PEI   FREQ≠)
  985 FORMAT(F4.2,I6,F9.2,I6,F9.2,I6,F9.2,I6)
      END
```

```
ALTERNATIVE NAME - BEAVERVILLE UNIT A - EXAMPLE DATA ONLY
NUMBER OF PRIMARY ATTRIBUTES -  2

IMPACTS ON WATER QUALITY

THERMAL SHOCK (HOT AND COLD)
RELATIVE WEIGHT =   .200
     0      .060      .100      .300      .500      .700      .900     1.100     1.300     1.500
     0      .050      .100      .200      .300      .600      .800      .950     1.000     1.000
  .010      .150      .250      .380      .500      .630      .750      .880      .990     1.000

DISSOLVED OXYGEN
RELATIVE WEIGHT =   .200
     0     1.000     2.000     3.000     4.000     5.000     6.000     7.000     8.000     9.000
 1.000      .950      .900      .850      .750      .500      .250         0         0         0
     0         0         0      .100      .200      .300      .500      .680      .900     1.000

RADIONUCLIDES
RELATIVE WEIGHT =   .200
 1.000     1.300     2.500     3.800     5.000     6.300     7.500     8.800    11.000    12.000
     0      .100      .200      .300      .400      .500      .600      .700      .800     1.000
  .010      .130      .250      .380      .500      .630      .750      .880      .990     1.000

IMPACTS ON AIR QUALITY

HYDROCARBON EMISSIONS
RELATIVE WEIGHT =   .400
  .900     2.200     3.000     4.000     4.500     5.000     6.000     7.000     8.600     9.200
  .050      .120      .190      .290      .390      .470      .600      .730      .880     1.000
  .010      .180      .400      .500      .660      .790      .880      .990     1.000     1.000
```

```
              ALTERNATIVE - BEAVERVILLE TEST DATA
              SIMULATION RESULTS FOR N = 1000

              MEAN PEI = .409   VARIANCE = .000529

  PEI     FREQ       PEI     FREQ       PEI     FREQ       PEI     FREQ
  .01      0         .26      0         .51      0         .76      0
  .02      0         .27      0         .52      0         .77      0
  .03      0         .28      0         .53      0         .78      0
  .04      0         .29      0         .54      0         .79      0
  .05      0         .30      0         .55      0         .80      0
  .06      0         .31      0         .56      0         .81      0
  .07      0         .32      0         .57      0         .82      0
  .08      0         .33      0         .58      0         .83      0
  .09      0         .34      0         .59      0         .84      0
  .10      0         .35      0         .60      0         .85      0
  .11      0         .36      6         .61      0         .86      0
  .12      0         .37     40         .62      0         .87      0
  .13      0         .38     79         .63      0         .88      0
  .14      0         .39    127         .64      0         .89      0
  .15      0         .40    137         .65      0         .90      0
  .16      0         .41    145         .66      0         .91      0
  .17      0         .42    146         .67      0         .92      0
  .18      0         .43    137         .68      0         .93      0
  .19      0         .44     96         .69      0         .94      0
  .20      0         .45     58         .70      0         .95      0
  .21      0         .46     26         .71      0         .96      0
  .22      0         .47      2         .72      0         .97      0
  .23      0         .48      1         .73      0         .98      0
  .24      0         .49      0         .74      0         .99      0
  .25      0         .50      0         .75      0        1.00      0
```

APPENDIX B

FORTRAN Listing and Data Specifications for OAI Simulation Program

Program OAISIM is designed to simulate values of the overall aggregate index (OAI) of each candidate alternative. Input data consists of discrete probability density functions describing the potential environmental impact (PEI) and equivalent uniform annual cost (EUAC) for each alternative.

The program determines the mean and variable of PEI and EUAC and standardizes these variables by the procedures described in Chapter VI. Simulation runs are then made for a maximum of ten selected R values. Each run can consist of up to 9999 simulation cycles. During each of these cycles, two randomly generated digits are used to determine PEI and EUAC values for each alternative and a simulated OAI is then calculated. The alternative with the minimum (most preferred) value is determined and relative frequencies of alternative preference are calculated. Output data also includes mean and variance for all OAI values simulated during the run.

INPUT DATA FORMS FOR PROGRAM OAISIM

Card Type	Field Description	Format
1	Number of Alternatives (NOAL)	I2
	-Maximum of ten per run	
	Code for optional printing of input data (KODE)	I3
	-Right adjusted in data field. '1' indicates data list desired, '0' indicates no list.	
	Number of simulation cycles (NSIM)	I5
	-Maximum of 9999 per run.	
	Number of R values to be simulated (NRVL)	I3 (3X)
	-Maximum of ten per run.	
	R Value array	10F4.2

2	Alternative Name -Maximum of 40 alphanumeric characters	20A2
3	Array of PEI values for alternative -Maximum of fifteen values	15F5.3
4	Array of discrete probabilities associated with PEI values	15F5.3
5	Array of EUAC values for alternative -Maximum of fifteen values	15F5.1
6	Array of discrete probabilities associated with EUAC values	15F5.3

Header and simulation run data is contained on the type 1 card. Each alternative to be included in the simulation requires cards of type 2 through 6.

```
      PROGRAM OAISIM
C
C     THIS PROGRAM IS DESIGNED TO PERMIT THE SIMULATION
C     OF AN OVERALL AGGREGATE INDEX (OAI) FOR A MAXIMUM
C     OF TEN ALTERNATIVES.  CURRENT DIMENSIONS ALLOW
C     PROBABILITY DENSITY FOUNCTIONS OF FIFTEEN INTERVALS
C     EACH FOR DESCRIBING THE DISTRIBUTIONS OF POTENTIAL
C     ENVIROMENTAL IMPACT (PEI) AND EQUIVALENT UNIFORM
C     ANNUAL COST (EUAC).  RELATIVE FREQUENCIES FROM
C     COMPARATIVE SIMULATIONS CAN BE OBTAINED FOR A MAXIMUM
C     OF TEN ≠R≠ VALUES PER RUN.  A MAXIMUM OF 9999 SIMULATION
C     CYCLES ARE PERMITTED FOR EACH R VALUE SPECIFIED.
C
C     PRIMARY VARIABLE NAMES
C
C     ABASE - STANDARDIZED AVERAGE PEI
C     ALNAM - ALTERNATIVE NAME
C     AOAI  - AVERAGE OAI VALUE
C     APEI  - AVERAGE PEI VALUE
C     AUAC  - AVERAGE EUAC VALUE
C     BBASE - STANDARDIZED AVERAGE EUAC
C     EUAC  - EQUIVALENT UNIFORM ANNUAL COST
C     KODE  - CODE FOR OPTIONAL PRINT OF INPUT DATA
C     NOAL  - NUMBER OF ALTERNATIVES
C     NRVL  - NUMBER OF R VALUES
C     NSIM  - NUMBER OF SIMULATION CYCLES
C     OAI   - OVERALL AGGREGATE INDEX
C     PAC   - PROBABILITY DENSITY OF PEI
C     PEI   - POTENTIAL ENVIRONMENTAL IMPACT
C     PPI   - PROBABILITY DENSITY OF PEI
C     RELF  - RELATIVE FREQUENCY
C     RVAL  - R VALUE FOR CALCULATION OF OAI
C     SOAI  - SUM OF OAI VALUES IN CYCLE
C     SPEI  - STANDARDIZED PEI VALUES
C     SUAC  - STANDARDIZED EUAC VALUES
C     VAA   - VARIANCE OF PEI VALUES
C     VAB   - VARIANCE OF EUAC VALUES
C     VAR   - VARIANCE OF OAI VALUES
C
      DIMENSION PEI(10,15),PPI(10,15),EUAC(10,15),PAC(10,15)
      DIMENSION SPEI(10,15),SUAC(10,15),ALNAM(10,20)
      DIMENSION APEI(10),AUAC(10),ABASE(10),BBASE(10)
      DIMENSION OAI(10),RVAL(10)
      DIMENSION SOAI(10),VAA(10),VAB(10)
      DIMENSION SOI(10),LEAD(10),VAR(10),AOAI(10),RELF(10)
      M=15
      READ(40,900)NOAL,KODE,NSIM,NRVL,(RVAL(I),I=1,10)
      DO 5 I=1,NOAL
      READ(40,910) (ALNAM(I,J),J=1,20)
      READ(40,930) (PEI(I,J),J=1,M)
      READ(40,930) (PPI(I,J),J=1,M)
      READ(40,920) (EUAC(I,J),J=1,M)
    5 READ(40,930) (PAC(I,J),J=1,M)
      DO 10 I = 1,NOAL
      SOI(I)=0.0
      VAR(I)=0.0
      APEI(I)=0.0
   10 AUAC(I)=0.0
      IF (KODE-1)14,11,14
C
C     STATEMENTS 11 THROUGH 13 ARE REQUIRED FOR OPTIONAL
C     PRINTING OF INPUT DATA LIST.  KODE = 1 ON FIRST
C     DATA CARD WILL INITIATE THIS SEQUENCE.
C
   11 DO 13 I=1,NOAL
      WRITE(61,950) I,(ALNAM(I,J),J=1,20)
      WRITE(61,955)(PEI(I,J),J=1,M)
      WRITE(61,960)(PPI(I,J),J=1,M)
      WRITE(61,965)(EUAC(I,J),J=1,M)
   13 WRITE(61,960)(PAC(I,J),J=1,M)
C
C     STATEMENTS 14 THROUGH 15 CALCULATE MEAN AND VARIANCE
C     OF PEI AND EUAC FOR EACH ALTERNATIVE
C
   14 DO 15 I=1,NOAL
      DO 15 J=1,M
      APEI(I)=APEI(I)+(PEI(I,J)*PPI(I,J))
      AUAC(I)=AUAC(I)+(EUAC(I,J)*PAC(I,J))
      SOI(I)=SOI(I)+(PEI(I,J)**2)*PPI(I,J)
      VAA(I)=SOI(I)-APEI(I)**2
```

```
      VAR(I)=VAR(I)+(EUAC(I,J)**2)*PAC(I,J)
   15 VAB(I)=VAR(I)-AUAC(I)**2
C
C     STATEMENTS THROUGH NUMBER 25 DETERMINE STANDARDIZED
C     VALUES OF PEI AND EUAC FOR EACH ALTERNATIVE AND
C     CREATE CUMULATIVE DISTRIBUTIONS OF STANDARDIZED VALUES
C
      ACNT=999.9
      BCNT=999.9
      DO 22 I=1,NOAL
      IF(ACNT-APEI(I))22,22,21
   21 ACNT=APEI(I)
   22 CONTINUE
      DO 24 I=1,NOAL
      IF(BCNT-AUAC(I))24,24,23
   23 BCNT=AUAC(I)
   24 CONTINUE
      DO 25 I=1,NOAL
      ATOT=0.0
      BTOT=0.0
      ABASE(I)=(APEI(I)/ACNT)*100.
      BBASE(I)=(AUAC(I)/BCNT)*100.
      OAI(I)=ABASE(I)+BBASE(I)
      DO 25 J=1,M
      SPEI(I,J)=(PEI(I,J)/APEI(I))*ABASE(I)
      PPI(I,J)=PPI(I,J)+ATOT
      ATOT=PPI(I,J)
      SUAC(I,J)=(EUAC(I,J)/AUAC(I))*BBASE(I)
      PAC(I,J)=PAC(I,J)+BTOT
   25 BTOT=PAC(I,J)
      WRITE(61,970)
      DO 27 I=1,NOAL
   27 WRITE(61,975)I,APEI(I),VAA(I),ABASE(I),AUAC(I),VAB(I),
     1BBASE(I),OAI(I)
C
C     IA, IC, AND IR ARE INITIALIZATION VALUES FOR RANDOM
C     NUMBER GENERATORS
C
      IA=4117
      IC=1772721
      IR=205205
      DO 100 NRC =1,NRVL
      DO 40 IA = 1,NOAL
      LEAD(IA)=0.0
      SOAI(IA)=0.0
   40 SQI(IA)=0.0
      DO 60 ICY = 1,NSIM
      DO 53 I=1,NOAL
C
C     RANDOM GENERATION OF STANDARDIZED PEI VALUE.
C     IR FUNCTION IS A UNIFORM RANDOM NUMBER GENERATOR
C     FOR THE CDC 3300.  FOR USE ON IBM EQUIPMENT,SUBROUTINE
C     RANDU MAY BE INSERTED AT THIS POINT.
C
      IR = AND(AND(IR*3085,8388607)+IC,8388607)
      PROB=FLOAT(IR)/8388607.
      DO 50 J=1,M
      IF(PPI(I,J)-PROB)50,51,51
   50 CONTINUE
C
C     RANDOM GENERATION OF STANDARDIZED EUAC VALUE.  SEE
C     COMMENT ON IR FUNCTION ABOVE.
C
   51 IR=AND(AND(IR*3085,8388607)+IC,8388607)
      PROB=FLOAT(IR)/8388607.
      DO 52 K=1,M
      IF(PAC(I,K)-PROB)52,531,531
   52 CONTINUE
  531 OAI(I)=SUAC(I,K)+(RVAL(NRC)*SPEI(I,J))
      SQI(I)=SQI(I)+OAI(I)**2
   53 SOAI(I)=SOAI(I)+OAI(I)
      STAN=9999.
      DO 55 I=1,NOAL
      IF(OAI(I)-STAN) 54,55,55
   54 NAT = I
      STAN = OAI(I)
   55 CONTINUE
   60 LEAD(NAT) = LEAD(NAT) + 1
      WRITE(61,980)RVAL(NRC),NSIM
      WRITE(61,985)
```

```
OS3 FORTRAN  VERSION 3.13 OAISIM    08/17/76  0850

C
C      STATEMENTS THROUGH NUMBER 64 CALCULATE MEAN, VARIANCE,
C      AND RELATIVE FREQUENCY OF OCCURANCE OF MINIMUM OAI
C      VALUES FOR EACH ALTERNATIVE.
C
       DO 64 I=1,NOAL
       VAR(I)=((SQI(I)/NSIM)-(SOAI(I)/NSIM)**2)
       AOAI(I)=SOAI(I)/NSIM
    64 RELF(I)=FLOAT(LEAD(I))/FLOAT(NSIM)
       DO 65 I=1,NOAL
    65 WRITE(61,990)I,AOAI(I),VAR(I),LEAD(I),RELF(I)
   100 CONTINUE
   900 FORMAT(I2,I3,I4,I3,3X,10F4.2)
   910 FORMAT(20A2)
   920 FORMAT(15F5.1)
   930 FORMAT(15F5.3)
   950 FORMAT(//≠  ALTERNATIVE ≠,I2,3X,20A2)
   955 FORMAT(≠  POTENT. ENVIR. IMPACT ≠15F6.3)
   960 FORMAT(≠  PROBABILITY≠,11X,15F6.3)
   965 FORMAT(≠  EQUIV. ANNUAL COST≠,4X,15F6.1)
   970 FORMAT(≠1≠//≠ ALTERNATIVE  AVERAGE   PEI    STAND.≠
      1≠  AVERAGE   EUAC   STAND.   OAI AT≠/16X,≠PEI    ≠
      2≠VARIANCE  PEI     EUAC   VARIANCE  EUAC    R = 1.0≠)
   975 FORMAT(/I7,F12.3,F10.6,F6.0,F9.1,F8.2,2F8.0)
   980 FORMAT(//≠1 SIMULATION RESULTS FOR R =≠,F5.2,≠ N =≠,I4)
   985 FORMAT(/≠ ALTERNATIVE   MEAN      OAI        ≠
      1≠MINIMUM  RELATIVE≠/15X,≠OAI     VARIANCE     OAI≠
      2≠     FREQUENCY≠)
   990 FORMAT(/I7,F12.1,F9.0,I10,F11.3)
       END
```

```
ALTERNATIVE  1   CORVALLIS UNIT A
POTENT. ENVIR. IMPACT   .310   .320   .330   .340   .350   .360   .370   .380   .390   .400   .410   .420   .430   .440   .450
PROBABILITY                0   .020   .030   .040   .050   .090   .110   .170   .150   .130   .110   .060   .030   .001      0
EQUIV. ANNUAL COST       8.0    9.0   10.0   11.0   12.0   13.0   14.0   15.0   16.0   17.0   18.0   19.0   20.0   21.0   22.0
PROBABILITY                0      0   .008   .086   .150   .166   .173   .186   .102   .095   .026   .006   .002      0      0

ALTERNATIVE  2   ROCKY RIVER UNIT D
POTENT. ENVIR. IMPACT   .610   .620   .630   .640   .650   .660   .670   .680   .690   .700   .710   .720   .730   .740   .750
PROBABILITY             .010   .020   .030   .040   .050   .100   .150   .200   .150   .100   .050   .040   .030   .020   .010
EQUIV. ANNUAL COST       6.5    7.0    7.5    8.0    8.5    9.0    9.5   10.0   10.5   11.0   11.5   12.0   12.5   13.0   13.5
PROBABILITY             .005   .010   .030   .040   .070   .090   .120   .270   .120   .090   .070   .040   .030   .010   .005

ALTERNATIVE  3   PHILOMATH UNIT E
POTENT. ENVIR. IMPACT   .260   .270   .280   .290   .300   .310   .320   .330   .340   .350   .360   .370   .380   .390   .400
PROBABILITY                0      0   .020   .030   .050   .100   .160   .280   .160   .100   .050   .030   .020      0      0
EQUIV. ANNUAL COST      11.0   12.0   13.0   14.0   15.0   16.0   17.0   18.0   19.0   20.0   21.0   22.0   23.0   24.0   25.0
PROBABILITY                0      0   .008   .086   .160   .180   .168   .186   .090   .088   .026   .006   .002      0      0

ALTERNATIVE  4   BIG CANYON UNIT G
POTENT. ENVIR. IMPACT   .460   .470   .480   .490   .500   .510   .520   .530   .540   .550   .560   .570   .580   .590   .600
PROBABILITY                0      0   .040   .060   .100   .160   .280   .160   .100   .060   .040      0      0      0      0
EQUIV. ANNUAL COST       8.5    9.0    9.5   10.0   10.5   11.0   11.5   12.0   12.5   13.0   13.5   14.0   14.5   15.0   15.5
PROBABILITY                0   .030   .050   .100   .140   .200   .180   .140   .080   .060   .020      0      0      0      0

ALTERNATIVE  5   BEAVER FLATS UNIT H
POTENT. ENVIR. IMPACT   .420   .430   .440   .450   .460   .470   .480   .490   .500   .510   .520   .530   .540   .550   .560
PROBABILITY                0   .020   .030   .050   .120   .160   .240   .160   .120   .050   .030   .020      0      0      0
EQUIV. ANNUAL COST       9.0    9.5   10.0   10.5   11.0   11.5   12.0   12.5   13.0   13.5   14.0   14.5   15.0   15.5   16.0
PROBABILITY                0      0   .020   .030   .090   .130   .160   .200   .160   .100   .070   .030   .010      0      0
```

```
ALTERNATIVE  AVERAGE    PEI      STAND.  AVERAGE    EUAC     STAND.   OAI AT
               PEI    VARIANCE    PEI     EUAC    VARIANCE   EUAC    R = 1.0

     1        .379    .001943    115      14.1      3.75      141      256
     2        .680    .000720    206      10.0      1.55      100      306
     3        .330    .000398    100      17.0      3.70      170      270
     4        .520    .000348    158      11.2      1.05      112      270
     5        .480    .000414    145      12.4      1.09      124      270
```

```
     SIMULATION RESULTS FOR R =   .40 N = 500
    ALTERNATIVE    MEAN      OAI       MINIMUM   RELATIVE
                   OAI     VARIANCE      OAI     FREQUENCY

         1        187.1      414         117        .234
         2        182.5      164         100        .200
         3        209.3      373           5        .010
         4        174.5      115         201        .402
         5        181.9      118          77        .154
```