

# Multi-criteria Decision Making in Water Resources Systems

H.P. Nachtnebel

**Abstract:** The objective of this lecture is to give a short summary about multi-criteria decision making techniques. The discussed techniques are by far not exhaustive and concentrate mainly on the case where a single decision maker has to solve a static problem. The kernel of the problem is that from a set of alternatives which have to satisfy a set of objectives characterised by different criteria and expressed in different units, the 'best alternative' has to be selected. This procedure requires the identification of the decision maker's preferences. The preferences can be differently expressed and are treated differently in the various techniques. Some small examples are given to demonstrate the methodological approaches.

## 1. Introduction and outline of the problem

In real world decision making there are always diverging or conflicting objectives which have to be satisfied as good as possible. To give some examples agricultural production should be increased and at the same time adverse outcomes like pollution of water bodies should be minimised; or a hydropower station should be planned in such a way that electric power production is as large as possible while the environmental impacts should be as small as possible; or mining activities should be developed in the most economically efficient way, providing labour and utilising all the resources in an environmentally sound way. Obviously, this set of objectives cannot be simultaneously satisfied and therefore preferences are required to compare the different quantities in outcome. The preferences should reflect the interests of the public and are expressed by the so called decision maker (DM). In this paper it is assumed that there is a single decision maker who takes the decision and an analyst who is elaborating the problem. Again these two assumptions are strongly simplifying reality because often we observe a group of decision makers having different preferences and often, also the problem itself is differently described by different groups. The latter case can be solved on a pure rational basis by expanding the scope of the problem so that each group is being represented in the analytical approach.

It is the responsibility of the DM to identify both the decision problem and specify the objectives of that problem (Gershon, 1981). It is also the DM who directly or indirectly furnishes the final value judgement that may be used to rank available alternatives, so that a satisfactum can be determined. The analyst, on the other hand, is responsible for defining the decision model, conducting the multi-criterion decision process and presenting the results to the DM. This requires that a wide range of activities be carried out by the analyst in the form of appropriate problem formulation, and quantitative and qualitative analyses of that problem (Fishburn, 1970; Zeleny, 1982; Goicoechea et al., 1982; Steuer, 1986;). In addition, some interactions between the DM and the analyst are indicated in these works.

The interaction between the analyst and the decision maker is an inherent characteristic of the decision process and its level is usually influenced by the DM's level of knowledge and willingness to participate in the process, the type of solution technique selected and the nature of the problem under consideration (Duckstein, 1984). The minimum interaction requirements are that the DM be able to specify his/her preference structure to the objectives of the problem under consideration, and then decide the acceptability of the solutions to the problem when presented to him/her by the analyst.

### **1.1 The DM's preference structure**

The weights and priorities in the decision makers' view represent the relative importance of the objectives or utilities of a problem to one another (Fishburn, 1970; Goicoechea et al., 1982) and thus constitute a major part of the DM's preference structure in a particular problem. Obviously, the preference structure of the DM has a major influence on the final evaluation results (Nachtnebel, 1994) and is always associated with subjectivity. Often it is difficult to express explicitly the preference structure and this implies that preferences are iteratively formulated. In case a particular set of weights does not result in a satisfactory solution, the weights can be changed in order to reach a more acceptable solution. The process of changing progressively or iteratively the weights until an acceptable solution is reached can help the DM to arrive at his/her "true" preference structure (Bogardi & Duckstein, 1992).

The ways how preferences can be expressed are given in chapter three.

### **1.2 The general structure of a decision making process**

The following 11 steps describe a general procedure in decision making (Duckstein, 1994).

(1) Whatever, the economic, social or environmental situation is unsatisfactory and asks for an action. In the ideal case this will stimulate the DM to provide clear verbal definitions of problem, of objectives and possible decision alternatives, or variables.

(2) Second, information is collected to assist in the decision making process. Often it is distinguished between hard and soft information. Hard data include information available in objective form, and can be obtained either from monitoring network data, through ambient monitoring and sampling, or from documents. Soft data, on the other hand, are subjective in nature, and may be obtained by polling individuals with expertise. Soft data may include measurements of un-quantifiable attributes, such as opinions, aesthetics, individual preference structures.

(3) The DM explicitly states the essential parts of the problem. This process includes specification of relevant criteria, establishment of the set of variables or feasible decision alternatives, and the definition of the problem constraints.

(4) Next, relations have to be established linking decision variables with outcomes (impacts). This relationship should be as quantitatively formulated as possible. In general, this step is based on physical laws, on simulation techniques which utilise models, or on expertise which gives empirical links among decision and output variables.

(5) This step deals with the choice of an appropriate multi-criteria decision making model (MCDM-model) to solve the problem. An appropriate MCDM solution procedure can be selected from a pool of available ones as long as it is able to handle the problem adequately. Further, it should also be appropriate to measure a DM's preferences with sufficient accuracy (Hobbs 1986).

(6) Once an appropriate solution technique has been selected which may be itself a multi-criterion problem, the next step may be to apply the technique to determine the set of efficient solutions by eliminating alternatives that are no better than any other alternative in all criteria, and are strictly worse in at least one criterion.

(7) Until now the procedure has been based on a more or less objective approach which means that any other group facing the same problem would achieve very similar results. Further it is necessary to discriminate within the non-dominated solutions to identify preferred solutions. Therefore, the DM's preference structure has to be specified and incorporated into a decision model.

(8) Now the MCDM-model is used to select one or more of the efficient alternatives. The outcomes associated to an alternative have to be explained and visualised in an intuitively understandable format and the related decision variables have to be listed and clearly described. This work is mostly done by the analyst.

(9) The solution is presented to the DM, who will decide whether to accept it. In this process, the DM subjectively assesses the value of the solution by taking into consideration other personal aspirations and other relevant external elements. These external elements include examination of the state of nature, and the environmental conditions affecting the decision process. If the solution is accepted, then it is ready for implementation, which refers to step(11).

(10) If the current solution does not satisfy the expectations of the decision maker, further interaction between the DM and the analyst is needed. This implies that constraints may be somewhat relaxed, that weights and preferences are reviewed and perhaps modified and that the DM may think to extend his objectives.

(11) The solution process ends when the DM is satisfied with the solution and accepts it for implementation.

## **2. Multi-criteria decision making techniques**

In this section, the frequently used decision making techniques are briefly summarised and classified. This may help in carrying out steps seven and eight of the MCDM procedure. The characteristics of the decision-making process can be classified accordingly to

- outranking techniques (for discrete alternatives only)
- distance-based techniques and
- value- or utility-based techniques.

Other classification schemes are proposed below which may assist in selecting an appropriate method.

Many useful and intuitively understandable tools exist which visualise the results in an appealing interactive structure (Loucks, 1994). Here, only the basic terminology is briefly described for a comprehensive representation of the analytical results. Any alternative  $A_i$  ( $i=1,N$ ) from the full set  $A$  is related to a subset of combined actions which are defined by the corresponding decision variables  $d_i$ . Then there are some objectives  $O_k$  ( $k=1,M$ ) which are expressed by a list of criteria  $C_j$ , ( $j=1,J$ ). Each objective is at least characterised by one criterion but in general several criteria describe the outcomes for one objective. Assuming an infinite number of actions the simplest visualisation by using the decision and objective space approach (Nachtnebel, 1999). In case of a discrete and countable set of alternatives the payoff table (or systems vs criteria matrix) can be used. In this table (matrix) each alternative is described in its outcomes by the set of criteria which are expressed in different units. So  $a_{23}$  is the outcome of alternative 3 with respect to criterion 2. Assume that criterion 2 expresses the net benefits then  $a_{23}$  is the net benefit from alternative 3. It is helpful to have in a similar table additional information which indicate, for instance the allocation of criteria to objectives.

Table 1: Payoff Matrix or Systems versus Criteria Array

Criteria	The full set of alternatives A				
	$A_1$	$A_2$	$A_3$	$A_i$	$A_N$
$C_1$	$a_{11}$	$a_{12}$	$a_{13}$	$a_{1i}$	$a_{1N}$
$C_2$	$a_{21}$	$a_{22}$	$a_{23}$	$a_{2i}$	$a_{2N}$
$C_3$	$a_{31}$	$a_{32}$	$a_{33}$	$a_{3i}$	$a_{3N}$
$C_j$	$a_{j1}$	$a_{j2}$	$a_{j3}$	$a_{ji}$	$a_{jN}$
$C_J$	$a_{J1}$	$a_{J2}$	$a_{J3}$	$a_{Ji}$	$a_{JN}$

In the case that we know the best and worst value for each criterion the table 1 can be scaled to the range 0,1. There are many procedures for scaling, one example can be in defining a utility function (Fig.1) (Keeney and Raiffa, 1976) and the other examples is a linear mapping .

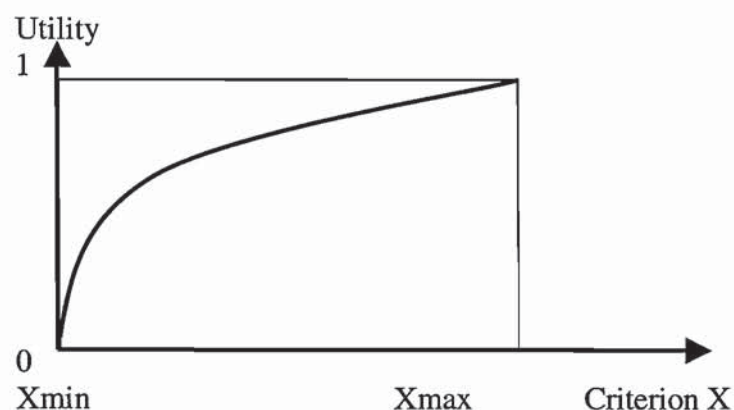


Figure 1: One-dimensional utility function

This utility expressed the DM 'value' of an outcome measured by criterion X. There are some axioms which a utility function has to satisfy (Keeney and Raiffa, 1976) the origins of this approach are to be found in Bentham and the axioms were established by Neumann and Morgenstern. In reality, we have to consider multi-dimensional utility functions (Multi-

attribute decision theory) which can be only elaborated by a rather sophisticated and time consuming interactive procedure between the DM and the analyst.

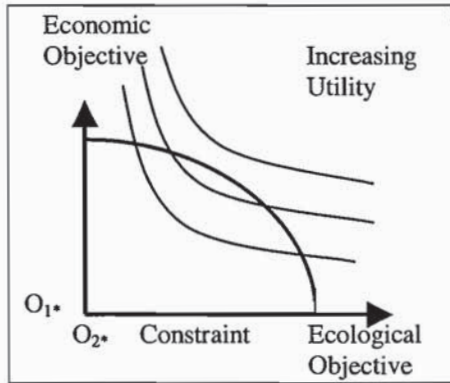


Fig. 2 Iso-Multiattribute Utility functions

Often a linear mapping procedure is applied which can be seen as equivalent to a linear utility function:

$$X' = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \quad \text{or} \quad Z = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Both variables  $X'$  and  $Z$  are within the range (0,1) and they are complementary to each other;  $X' + Z = 1$

$X'$  expresses the degree of dis-satisfaction and  $Z$  corresponds to the degree of satisfaction.

Later on, some additional tables will be used for the selection and ranking procedure.

### 3. Outranking MCDM Techniques

These techniques use outranking relationships among alternatives to select the most "satisfying" alternative. An outranking relation represents the pairwise preference ordering of a finite set of alternatives. Four different preference relations between a pair of alternatives can be defined: a strict preference, indifference, weak preference, and incomparability (Roy and Vincke 1984).

Given two alternatives  $A1$  and  $A2$  belonging to the full set of alternatives  $A$ , a strict preference between  $A1$  and  $A2$  implies that one of them is significantly preferred to the other, that is,  $A1 > A2$  or  $A2 > A1$ , but not both. Here, ' $>$ ' stands for the strict preference relation. In contrast, we have the indifference relation when the difference between alternatives  $A1$  and  $A2$  becomes too small to be recognisable. In this case, the two actions are indifferent in the sense that  $A1 = A2$  and  $A2 = A1$ , where '=' represents the equivalence relation. When the difference between alternatives is neither sufficiently small, so as to be indifferent, nor sufficiently large, as to constitute a strict preference, they are known as a weak preference, a concept introduced by Roy (1973) to describe the situation. A possible way of formal description can be  $A1 (>><) A2$  or  $A2 (<<>) A1$ . On the other hand, when the attributes between alternatives are significantly different from each other and the DM does not have

adequate information to compare them, then the alternatives are said to be incomparable with each other. The relation of incomparability can be represented by  $A1.ic.A2$  or  $A2.ic.A1$ .

Using the above four distinct preference relations, the outranking relation between any two alternatives  $A1$  and  $A2$  in  $A$  can be defined. Two types of outranking relations are recognised: a deterministic outranking relation, and a fuzzy outranking relation (Roy 1977; see also Nachtnebel, 1992). A deterministic out-ranking relation asserts that, given alternatives  $(A1,A2) \in A$ ,  $A1$  outranks  $A2$  ( $A1 \succ A2$ ) if there exists sufficient evidence that alternative  $A1$  is at least as good as alternative  $A2$  and there is no good reason to reject it. As far as deterministic outranking relationships are concerned, there is no discrimination between strict preference and weak preference. On the other hand, a fuzzy outranking relation provides more information than the deterministic one, since the credibility of the outranking of one alternative on another is also given (see Roy, 1977).

An example of an outranking method is ELECTRE I (Benayoun et al. 1966). An alternative  $A1$  is said to outrank  $A2$  if  $A1$  is better than  $A2$  in a sufficient (weighted) number of criteria, and if  $A1$  is not too much worse than  $A2$  in any of the other criteria. This means that two columns 1 and 2 are selected for comparison from the payoff table. Each criterion has a weight expressing its importance. Two indicators, the concordance index  $CI$  and the discordance index  $DI$  are defined to express this fact more precisely. The Concordance Indicator expresses the dominance and the Discordance Indicator describes how strong an alternative fails in the comparison. Both indicators have the range  $(0,1)$ . So an 'alternative  $i$  is better than  $j$ ' when the  $CI$  is as close as possible to 1 and the  $DI$  as close as possible to 0.

Table 2: Extended Pay-off Table with Weights and Scales

Criteria	$A_1$	$A_2$	$A_3$	$A_i$	$A_N$	Worst	Best	Weight	Scale
$C_1$	$a_{11}$	$a_{12}$	$a_{13}$	$a_{1i}$	$a_{1N}$	$C_{1Min}$	$C_{1Max}$	$W_1$	$Sc_1$
$C_2$	$a_{21}$	$a_{22}$	$a_{23}$	$a_{2i}$	$a_{2N}$	$C_{2Min}$	$C_{2Max}$	$W_2$	$Sc_2$
$C_3$	$a_{31}$	$a_{32}$	$a_{33}$	$a_{3i}$	$a_{3N}$	$C_{3Min}$	$C_{3Max}$	$W_3$	$Sc_3$
$C_j$	$a_{j1}$	$a_{j2}$	$a_{j3}$	$a_{ji}$	$a_{jN}$	$C_{jMin}$	$C_{jMax}$	$C_j$	$Sc_j$
$C_J$	$a_{J1}$	$a_{J2}$	$a_{J3}$	$a_{Ji}$	$a_{JN}$	$C_{JMin}$	$C_{JMax}$	$C_J$	$Sc_J$

$$CI(i, j) = \frac{\sum_{A_i > A_j} w_k + \frac{1}{2} \sum_{A_i = A_j} w_k}{\sum w_k}$$

$$DI(i, j) = \text{Max}_{k=1, J} \left\{ \frac{Z_{ki} - Z_{kj}}{\text{Max}(Sc)} \right\} \text{ for all } A_j > A_i$$

This approach will result in a partial outranking and by defining some threshold levels for  $CI$  and  $DI$ , namely  $p$  and  $q$ , those alternatives are considered where  $CI(i,j) > p$  and  $DI(i,j) < q$ . Extensions of the method can be found in Roy (1971;1973;1974,1975;1978). Some examples and details of the methodology can be found in Nachtnebel (1994)

This group of outranking techniques is only applicable in the case of discrete alternatives. The strength is in the fact that also qualitative criteria can be treated.

## 4. Distance-Based MCDM Techniques

Some MCDM techniques use the concept of distance to choose a satisfying solution. Most of these methods choose the alternative that minimises some measure of distance between the alternative and reference set of criteria values. Distances are used as a proxy measure for human preference (Zeleny, 1981). Distances show the degree of resemblance, similarity, or proximity of alternatives with respect to individual criteria.

There are several distance-based techniques that have been developed. Generally, these techniques proceed first by defining some reference point, which, in most cases, should be an infeasible alternative to which the alternatives are related. One major difference among the techniques that belong to this group is the way they relate to the reference point. Compromise programming (CP) finds the feasible solution that is closest to an ideal solution. Other techniques, such as co-operative game theory (CGT), on the other hand, use quite a different concept of distance to determine an acceptable solution. Another group of techniques, which also use the concept of minimum-distance, are goal programming and its variants.

### 4.1 Compromise Programming

As an example of a distance-based method, the compromise programming technique is summarised. In determining the most satisfying solution by this method, the ideal solution can be defined as the vector  $C^*=(C_{1max}, C_{2max}, C_{imax}, C_{Jmax})$ , where the  $C_{i,Max}$  is the best value (see table 2) across alternatives  $X \in A$ , of criterion  $i$ . A commonly used measure of closeness in this method is a family of  $L_p$  metrics (Duckstein and Opricovic 1980; Zeleny 1973; Zeleny 1981; Szidarovszky et al. 1986) which measure the distance of alternative  $A_i$  from the 'Ideal Point'  $C^*$ .

$$L_p(i) = \sum_{k=1, J} (w_k (C_{ki} - a_{ki})^p)^{1/p}$$

where the weights  $w_k > 0$  indicate the relative importance of the objectives to the DM and the value  $p$ , which has nothing to do with the  $p$ -value being used as a concordance threshold, may range from  $1 \leq p \leq \infty$ . The exponent  $p$  defines the metrics of the system. For instance, using a value  $p=1$  would correspond to defining the distance by the mean distance, while  $p=2$  corresponds to a metric distance. For  $p = \infty$ , the largest of the deviations completely dominates the distance measure, or in other words, the distance of an alternative to the 'ideal solution' is dependent on its largest component. Consequently, Eq. 3 reduces to the expression:

$$L_{p=\infty}(i) = \max_k [C_{ki,max} - a_{ki}(x)], k = 1, 2, \dots, J$$

Independent from the value  $p$  which is related to the attitude of the DM towards risk, the 'best alternative' is identified by its smallest distance from the ideal point. So the objective is to find

$$L_{p,Min} = \text{Min}\{L_p(i)\} \text{ for all } i = 1, N$$

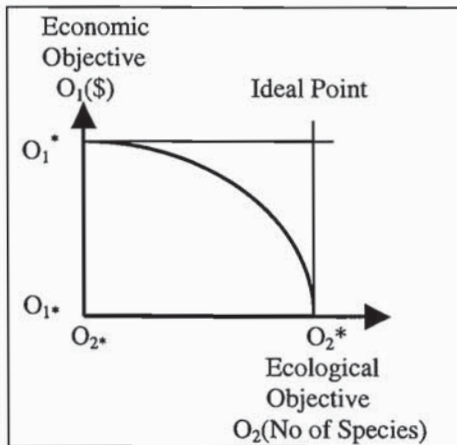


Fig. 3 Compromise Solutions are Identified by the Smallest Distance to the Ideal Point

#### 4.2 Goal Programming

By contrast, goal programming chooses the alternative that minimises the distance to a predefined set of goals  $G_i$ , which are chosen by the decision maker and do not have to equal the Ideal Point.

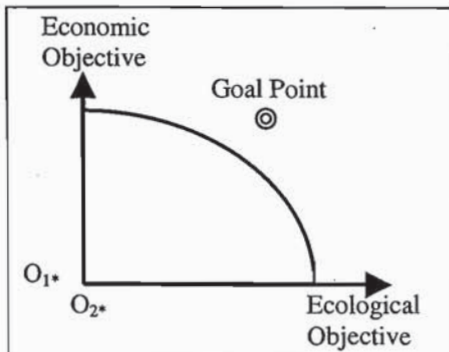


Fig. 4 Goal Programming

Goal programming allows the DM to specify a target for each objective function. A preferred solution is then defined as the one that minimises the sum of the deviations from the prescribed set of target values. The team of A. Charnes and W.W. Cooper (1961) is generally credited with the development of the goal programming method and has played a key role in applying the method to industrial problems. It may be noted that the initial purpose of developing the method was multiple-objective decision making, but its subsequent use may justify the credit generally given to Charnes and Cooper for pioneering in the field.

Assume that the decision maker is able to specify an  $J$ -dimensional vector  $C^* = (C_1^*, C_2^*, C_1^* \dots C_J^*)$  which is considered as a desirable if not ideal set of simultaneous objective function (or criteria) values. This vector  $C^*$  is called the "goal point" and can be interpreted as the decision maker's optimistic estimation of the simultaneous values of the objective functions. If for  $j=1, \dots, J$ ,  $C_j^*$  is the maximum value of  $C_{jMax}$  then vector  $C^*$  is called the ideal point.



If  $C^*$  is feasible, then it is reachable, and the corresponding decisions can be determined by solving the equations

$$\begin{aligned} O_1(x) &= C_1^* \\ &\dots\dots \\ &\dots\dots \\ O_2(x) &= C_j^* \end{aligned}$$

For the continuous case with an infinite number of alternatives we cannot use anymore the table 1 or 2. Therefore the following approach has to be used where  $O_1$  and  $O_2$  correspond to the objective functions and  $x$  stands here for the decision and input variables.

If  $C^*$  does not belong to the feasible pay-off set, then we must find a feasible pay-off vector which is as close as possible to that point. The techniques realising this principle are based on different measures of distance between a feasible pay-off vector and the goal point. In the practical applications, therefore one of the following single objective programming problems is usually solved.

**Minimax Solutions:**

$$\text{MinMax}\{w_1|C_1^* - O_1^*(x)|; w_k|C_k^* - O_k^*(x)|; w_J|C_J^* - O_J^*(x)|\}$$

**Weighted Distance Function**

$$\text{Minimize}\left\{\sum w_i|C_i^* - O_i(x)|\right\}$$

Obviously these two approached, namely goal programming and compromise programming, have several features in common.

**4.3 Value- or Utility-Type of MCDM Techniques**

In addition to the explanation of the utility-type approach given in the chapter 2. some further information is provided here.

These MCDM procedures attempt to model mathematically a DM's preference structure by a value function (if the problem is deterministic), or utility function (if there is any risk involved in the problem). Multiattribute utility theory, as described by Keeney and Raiffa (1976), is a utility-type MCDM technique, which is based on the above axioms of utility theory. An example of a multiattribute utility function is:

$$\max U(X) = \sum w_i U_i(x_i)$$

where  $U(X)$  is the overall utility of an alternative  $X$ ,  $X$  being described by a vector of attributes  $\{x_i\}$ .  $U_i(x_i)$  is a single attribute value function, translating attribute  $x_i$  into a measure of utility (see Fig. 1), and  $w_i$  as its weight. The weights are key to this method, and should be chosen so that they represent the decision maker's willingness to trade off the attributes. For example, if the DM is willing to give up 0.2 units of  $U_1(x_1)$  to obtain an improvement of just 0.1 in  $U_2(x_2)$  the weight of  $x_2$  should be twice that of attribute 1 (Keeney and Raiffa 1976; Hobbs 1980).

## 5. Example for a small hydropower plant

In this example, the operation of a small-scale hydropower scheme is investigated (see also Bogardi and Nachtnebel, 1994). The problem has the following features:

- A compromise is to be found between conflicting economic and environmental objectives measured by two aggregate sets of criteria.
- Various uncertainties are present.

### 5.1 Description of the case study

A diversion type hydropower plant has to be designed in such a way that the amount of water diverted from the river should maximise hydropower production and at the same time the remaining discharge in the river bed should be as large as possible to minimise adverse environmental impacts. The compensation discharge  $Q_C$  is the minimum discharge in the old riverbed which must be released by the operator of the scheme in any case downstream the weir.

The existing guidelines for deciding upon discharge are based on economic criteria, yet the adverse environmental effects are of great importance. As a consequence of the domination of economic criteria, the runoff is diverted over long river sections to such an extent that the riverbed falls dry during the summer and autumn season. Only the flood runoff is observed in the riverbed within that period. A drastic degradation of the aquatic environment is thus bound to occur unless a compensation discharge is released. Yet guidelines to determine such compensation discharge are lacking (Harboe et al. 1980; Schlußbericht 1982; Bayerisches Landesamt 1983; Duckstein et al. 1988).

Due to the fact that both environmental and economic concerns are adversely affected by the amount of the compensation discharge, a compromise must be achieved to resolve the conflict. In this study, the decision variable is taken solely as the compensation discharge, which generates the set of alternatives. There are several other possible actions, such as selecting the length of the diversion channel, or the length of the impounded river section upstream from the weir, which are not considered herein.

An existing hydropower scheme located at the river Erlauf in Lower Austria (Fig. 1) has been selected as an example. It has an installed capacity of 1.07 MW, generates 5.17 GWh/year, possesses a 1,100 m diversion channel, is bypassing a 2,200 m river section, and is designed for a that this discharge is exceeded 90 days in a year as compared to the mean annual discharge of 13.9 m<sup>3</sup>/s. The prescribed minimum release of 0.05 m<sup>3</sup>/s downstream represents an insufficient quantity to maintain the viability of the aquatic system.

The mean annual low flow is estimated at 3.8 m<sup>3</sup>/s, while the lowest observed runoff is 1.87 m<sup>3</sup>/s. This river is highly attractive for sport fishery and represents an excellent habitat for trout and grayling. The water quality is good and only low biochemical oxygen demand (BOD) loads occur. The annual cycle in runoff, and in air and water temperatures, indicates that critical periods caused by low flow with simultaneously increased water temperature will occur from June 1 to September 30.

### 5.2 Objectives

The two vectors of objectives and their components are now explained. The economic objective has two components: first, a monetary benefit, and second, a cost represented by the number of days of shutdown because of water shortage. The second component is of particular importance for locally operated power stations. Thus, the first objective function vector to be maximized is

$$O_1 = (a_{11}, a_{12}) = (ANB, -OPD)$$

where ANB = annual net benefits and OPD = days shut down per year. Cost functions for construction and operation works are derived either from published data (Gordon 1983) or available data from plants with similar capacity.

The environmental objective  $O_2$  tries to preserve the environmental functions of the diverted section and includes the environmental consequences corresponding to the following components:

- $a_{21}$ : Increase in water temperature TW.
- $a_{22}$ : Change in dissolved oxygen concentration  $O_2$
- $a_{23}$ : Change in water depth H.
- $a_{24}$ : Reduced water body volume VOL.
- $a_{25}$ : Variation in river width (variance).

The negative consequences of changes in these five components should be minimized to prevent any degradation of the river section.

### 5.3 State Variables

The state variables describe the system at time  $t$  and include: water temperature and dissolved oxygen concentration, which characterise the water quality; morphometric measures such as water depth, volume of the water body, and variation in the river width, which describe the state of the environment. Water depth is a simple measure for the aquatic habitat and also accounts for fish passage. The total volume of the water body is a criterion representing environmental quality for the remaining aquatic habitat. The variation of river width constitutes a valuable indicator for the variety of fish species and their respective population densities.

### 5.4 State Equations

Next, for each river section, a set of state equations similar to the QUAL II-model (U.S. EPA: User's Manual 1981) is developed to estimate the state and output from the environmental subsystem. Further details may be found in Nachtnebel et al. (1986). The complete set of equations consists of a hydraulic equation, an energy balance equation, and a dissolved oxygen balance equation.

### 5.5 Input

As stated earlier, the controllable input is the compensation discharge  $QC$ . The noncontrollable, or natural, input includes meteorological data, such as global radiation, long wave radiation, wind velocity and frequency, frequency of cloudiness, air temperatures, and

air humidity. The set of hydrologic input variables consists of the runoff pattern, water temperature, and BOD load, together with dissolved oxygen and algae biomass concentration. The required topographic input is given by six cross sections, a longitudinal section of the riverbed, the flow direction, and the flow velocity for each section, the riparian lands, and their vegetative cover. This last description accounts for a reduced radiation exposure of the water table.

## 5.6 Environmental Value Functions

Due to a lack of consensus in setting proper evaluation scales for the environmental indicators, value functions are assessed to indicate the degree of worth, or relevancy, of a certain environmental indicator for a sound environment. For example, the increase in water temperature will be considered to have a value of 1.0, if experts rate the increase as "good." The dissolved oxygen concentration is evaluated similarly to the value function in Dee et al. (1972). The water depth and the water volume are evaluated by a piecewise linear function. The water volume value function refers to the change in volume, while the water depth is given in absolute values.

Table 3: Weights and Parameters in Objective Functions of Erlauf River Problem

Objective	Weights		CP parameter
Economic ( $O_1$ )	$w_{11} = 0.8;$	$w_{12} = 0.2$	$p_1 = 2$
Environmental ( $O_2$ )	$w_{2j} = 0.2;$	for $j = 1, . 5$	$p_2 = 4$
Overall ( $O_o$ )	$W_1 = 0.5;$	$W_2 = 0.5$	$q = 2$

## Randomness

To incorporate the stochastic component into the decision process, a Monte Carlo simulation approach has been selected. A series of 300 summer runoff events, including a simulation of model inputs as described in the previous section, was generated to analyse the randomness in the environmental degradation due to water intake.

## Aggergation of criteria

Next, the set of criteria characterising each of the two objectives are to be aggregated, and then the two objectives are to be traded off in a two-level, distance-based procedure called composite programming (Bardossy et al. 1985; Bogardi et al 1984), in which compromise programming is first applied within each objective, and then again between the two aggregate objectives, as shown below in the following equations. The  $L_p$  norms for the two aggregated objective functions monetary benefit ( $O_1$ ) and environment ( $O_2$ ) are written, respectively, as (Nachtnebel et al. 1986),

$$O_1 = \left( w_{11} \left| \frac{ANB^* - ANB}{ANB^* - ANB_*} \right|^{p_1} + w_{12} \left| \frac{OPD_* - OPD}{OPD_* - OPD^*} \right|^{p_1} \right)^{1/p_1}$$

$$O_2 = \left[ \sum w_{2i} \cdot [V_{2i}(C_{2i}^*) - V_{2i}(C_{2i})]^{p_2} \right]^{1/p_2}$$

where a superscript \* indicates the best value of a component, and a subscript \* designates the least desirable value.

The overall composite goal function is written as:

$$O_0 = (W_1 F_1^q + W_2 F_2^q)^{1/q}$$

In each group of indicators, a compromise programming (CP) parameter  $p_i$  and a set of weights  $w_{ij}$  is to be defined. The economic weights given in Table 3 reflect the dominance of annual net benefits over the number of shutdown days per year.

The environmental indicators are of equal importance, but, due to limiting character of the worst indicator, a value  $p_2 = 4$  is selected for the trade-off among the environmental elements. Factor  $p_2 = \infty$  would indicate that the environmental quality is always determined by the worst case.

## 5.7 Results

To display the influence of the weights, trade-off curves, such as the one shown in Fig. 5 for a typical summer day, were derived. In Fig. 3, the observed discharge was given as 8.71 m<sup>3</sup>/s. Any reduction of the discharge results in a worsened value for one or more of the environmental indicators. The trade-off curve was obtained by variation of the weights  $W_i$ . A value of  $W_1 = 1$  considers only economic aspects, yielding maximal net benefits. With equal weights  $W_i$ , a compensation discharge of 1.86 m<sup>3</sup>/s would be necessary. The curve in Fig. 3 was obtained under the assumption that plant capacity had not been set previously; in other words, a new scheme is to be installed with a capacity determined by the compromise solution. Assuming equal weights for the two objectives yields a minimum release of 1.86 m<sup>3</sup>/s. Even if the weight for the economic objective is nine times higher than that of the environmental objectives, a minimum release of 0.88 m<sup>3</sup>/s is still found to be necessary.

### Effect of Randomness

Based on a Monte Carlo simulation that utilises the available information obtained from the hydro-meteorological network, the consequences of a series of 300 simulation inflow events were analysed. Due to randomness in the hydrologic and meteorological variables, the composite programming approach yields different solutions for the same set of weights. In particular, an expected value solution for QC may constitute an overdesign or an underdesign. With  $W_1 = W_2 = 0.5$ , the minimum required release downstream of the weir is 1.72 m<sup>3</sup>/s, while 90% of the simulated events exhibit a discharge of 1.80-1.90 m<sup>3</sup>/s. In two percent of the simulated results, the compensation discharge range varies from 2.0-2.5 m<sup>3</sup>/s. The cumulative distribution of the compensation discharge QC is also sketched in Fig. 4. On the basis of this distribution, with a prespecified failure probability, a final compromise decision can be made given  $W_1 = W_2 = 0.5$  in the overall objective function.

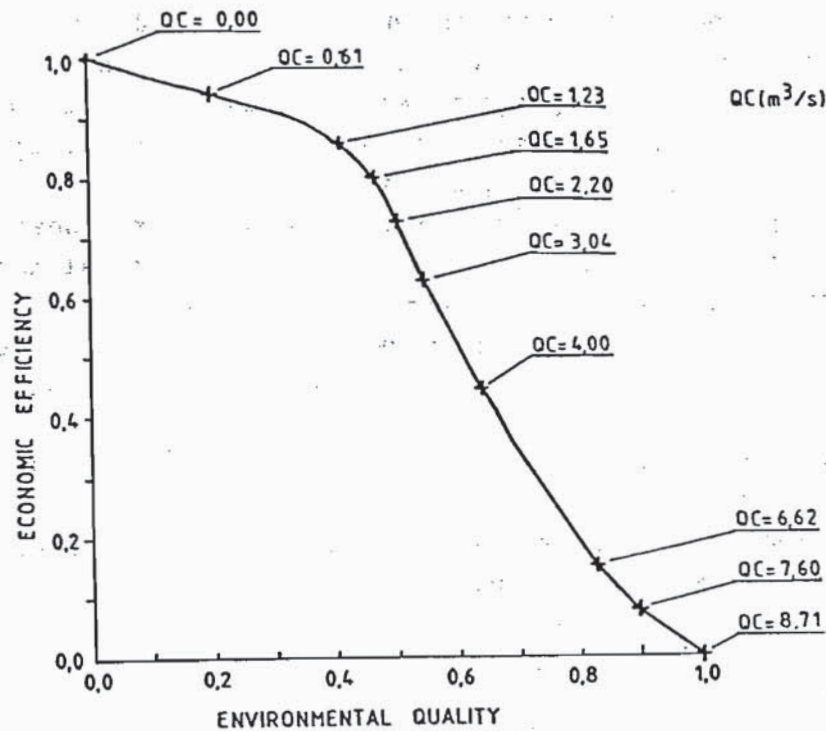


Fig. 5. Nondominated Solutions Derived for Typical Summer Day ( $Q = 8.71 \text{ m}^3/\text{s}$ )

Optimising with respect to the expected value results in a compensation discharge of  $1.8 \text{ m}^3/\text{s}$ . Accepting a 2 % environmental failure probability requires a release of at least  $2.0 \text{ m}^3/\text{s}$ . The release presently prescribed by law is  $0.05 \text{ m}^3/\text{s}$ . The owner of the plant releases at least  $0.2 \text{ m}^3/\text{s}$  into the river to avoid drastic degradation of the environment; this is about one order of magnitude smaller than QC found in the present multiobjective study.

Other procedures proposed to estimate the necessary compensation discharge are often related to hydrological parameters derived from the flow duration curve. For example, one may select 5-10% of mean daily discharge, which yields QC in the range  $0.67\text{-}1.35 \text{ m}^3/\text{s}$ .

As an outcome of this study, the owners of this power facility, and of other similar ones, have indeed increased the compensation discharge to nearly 70 % of the recommended figure. Also, the law is being modified to prescribe considerably higher compensation discharge in future plants. In any case, displays are of great help to explain and classify to practitioners the tradeoffs between hydropower production and environmental effects.

## 5.8 Conclusions

1. The proposed procedure accounts for both randomness and subjective values in the evaluation of environmental consequences.
2. The composite programming approach appears to be an appropriate technique for problems that possess different groups of criteria pertaining to each objective.
3. The proposed procedure appears to lead a rational selection of the compensation discharge; that is, the minimal amount of water that must be released downstream from the weir.

4. The bi-objective framework also satisfies environmental concerns, thus preventing any drastic degradation of the river section.
5. The input data consists of hydrological and meteorological information, which can easily be obtained.
6. The randomness associated with the design process is explicitly taken into account by a simulation procedure. The frequency of failure of an average optimum policy can thus be estimated.
7. A substantially higher compensation discharge is obtained than the one corresponding to existing guidelines.

## References:

- Bayerisches Landesamt für Wasserwirtschaft (1983). "Nutzen-Kosten-Untersuchung für Teilrückleitung des oberen Isar." Bericht Nr. IV/4-4439.1, Munich, Germany (in German).
- Benayoun, R., Roy, B., and Sussman, N. (1966). "Manual de reference du programme electre." Note de Synthese et Formation, No. 25, Direction Scientifique SEMA, Paris, France (in French).
- Bogardi, J.J. & Duckstein, L. (1992) Interactive Multiobjective analysis embedding the decision maker's implicit preference functions. Invited paper prepared for the special issue of Water Resources Bulletin titled Multiple Objective Decision-Making in Water Resources.
- Chankong, V. & Haimes, Y.Y. (1983) Multiobjective Decision Making: Theory and Methodology. Elsevier-North Holland, New York.
- Chankong, V., and Haimes, Y. Y. (1983). Multiobjective decision making: Theory and methodology. Elsevier-North Holland, New York, N.Y.
- Charnes, A. and Cooper, W.W.(1961) Management models and industrial applications of linear programming. J. Wiley and Sons, NY, USA.
- Cohon, J.L. (1978) Multiobjective Programming and Planning. Academic Press, New York.
- Dee, N., et al. (1972). "Environmental evaluation system for water resource planning." Battelle Columbus Laboratories, Columbus, Ohio.
- Duckstein, L. & Bogardi, I. (1988) Multiobjective approaches to river basin planning. Handbook of Civil Engineering. Technomic Publishing, Hasbrouck Heights, New Jersey, pp. 415-452.
- Duckstein, L. (1984) Selection of Multiobjective Technique for Water Resources Problem Under Uncertainty. In: Haimes, Y.Y. & Allee, D.J. (eds.), Multiobjective Analysis in Water Resources, American Society of Civil Engineers, New York, pp. 179-202.
- Duckstein, L. (1994) Value and Utility Concepts in Multi-criteria Decision Making. In: In: Bogardi, J.J. and Nachtnebel, H.P. (eds) Multi-criteria Decision Analysis in water Resources Management. UNESCO Publ. SC94/WS.14. UNESCO, Paris.
- Duckstein, L., and Opricovic, S. (1980). "Multiobjective optimization in river basin development. " Water Resour. Res., 16(1), 14-20.
- Fishburn, P.C. (1970) Utility Theory for Decision Making. John Wiley and Sons, New York, 234 p.
- Gershon, M. (1981) Model Choice in Multiobjective Decision Making in Water and Mineral Resources Systems. Natural Resource Systems Technical Rpt. Series No. 37. Dept. of Hydr. and Water Resources, University of Arizona, Tucson, Arizona.
- Gershon, M. E., and Duckstein, L. (1983). "Multiobjective approaches to river basin planning." J. Water Resour. Plng. and Mgmt., ASCE, 109(1), 945-967.

- Goicoechea, A., Hansen, D. R., and Duckstein, L. (1982). Multiobjective decision analysis with engineering and business applications. J. Wiley and Sons, New York, N.Y.
- Goicoechea, A., Hansen, D.R. & Duckstein, L. (1982) Multiobjective Decision Analysis with Engineering and Business Applications. John Wiley & Sons, New York, 519 p.
- Haimes, Y.Y. & Hall, W.A. (1974) Multiobjectives in Water Resources Systems Analysis: The Surrogate Worth Trade-off Method. *Water Resources Research* 19(4), 615-624.
- Harboe, R., Schultz, G., and Duckstein, L. (1980). Low-flow and flood control: distributed versus lumped reservoir model. *Proc., Symp. on Water and Related*
- Hobbs, B. (1980). "Multiobjective power plant siting methods." *J. Energy Engrg. Div., ASCE*, 106(2), 187-200.
- Hobbs, B. (1986). "What can we learn from experiments in multicriteria decision analysis?" *Trans. Systems, Man, and Cybernetics, Inst. of Electrical and Electronic Engrs ., SMC-16(3), May-Jun., 410-425.*
- Keeney, R. L., and Raiffa, H. (1976). Decisions with multiple objectives: Preferences and value tradeoffs. John Wiley and Sons, New York, N.Y.
- Loucks, D.P.(1994) IRIS an Interactive Decsion Tool for Water Resources Management. In: Bogardi, J.J. and Nachtnebel, H.P. (eds) Multi-criteria Decision Analysis in water Resources Management. UNESCO Publ. SC94/WS.14. UNESCO, Paris.
- Markowitz, H. (1959). Portfolio selection. John Wiley and Sons, New York, N.Y.
- McCuen, R. H., and Moglen, G. E. (1988). "Multicriterion stormwater management methods. *J. Water Resour. Plng . and Mgmt., ASCE*, 114(4), 414-431.
- Nachtnebel, H. P., Hanisch, P., and Duckstein, L. (1986). "Multicriterion design of small hydropower plants. *Annals of Reg. Sci., XX(3), 86-100.*
- Nachtnebel, H.P. (1994) Multi-criterion decision making methods with ordinal and cardinal scales. In: Bogardi, J.J. and Nachtnebel, H.P. (eds) Multi-criteria Decision Analysis in water Resources Management. UNESCO Publ. SC94/WS.14. UNESCO, Paris.
- Nachtnebel, H.P. (1999) Lecture Notes for the Short Intensive Course on Water Related Decision Making. Altai State Technical Universty, Barnaul, Russia.
- Roy, B. & Bertier, B. (1971) La methode ELECTRE II: une methode de classement en presence de criteres multiples. Note de travail No. 142. Groupe METRA, LAMSADE, Univ. Dauphine, Paris.
- Roy, B. (1973) How outranking relation helps multiple criteria decision making. In Cochrane J.L. and Zeleney M. (Eds.) Multi Criterion Decision Making. University of South Carolina Press, SC. Roy, B. (1978) ELECTRE III: un algorithm de classement fonde sur une representation floue de preference en presence de criteres multiples. *Cahiers Centre Etudes Recherches Operationelle, LAMSADE, Paris*, 20, 1, 3-24.
- Roy, B. (1973). "How outranking relation helps multiple criteria decision making. Multiple criteria decision making, J. L. Cochrane and J. Zeleny, eds., University of South Carolina Press, Columbia, S.C.
- Roy, B. (1977a). "Partial preference analysis and decision aid: The fuzzy outranking relation concept. *Conflicting objectives in decisions*. D. Bell, R. Keeney and H. Raiffa, eds., John Wiley and Sons, New York, N.Y.
- Roy, B. (1977b). "Conceptual framework for a normative theory of decision aid. Multiple criteria decision making, M. Starr and M.Zeleny, eds., North Holland, Amsterdam, The Netherlands.
- Roy, B., and Vincke, P. H. (1984). "Relational systems of preference with one or more pseudo-criteria: Some new concepts and results." *Mgmt. Sci.*, 30(11), 1323-1335.
- Schlußbericht der interdepartementalen Arbeitsgruppe Restwasser. (1982). E. Akeret, ed., Eidgenössisches Department des Inneren, Bern, Switzerland.
- Steuer, R.E. (1986) Multiple Criteria Optimization: Theory, Computation, and Application. John Wiley & Sons, New York, 546p.



- Szidarovszky, F., Gershon, M. E., and Duckstein, L. (1986). Techniques for multiobjective decision making in systems management. Elsevier, Amsterdam, The Netherlands.
- Zeleny, M. (1973) Compromise Programming. In: Cochrane, J.L. and M. Zeleny (eds.), Multiple Criteria Decision Making, University of South Carolina Press, Columbia, South Carolina, 263-301.
- Zeleny, M. (1973). "Compromise programming. Multiple Criteria Decision Making, J. L. Cochrane and M. Zeleny, eds., University of South Carolina Press, Columbia, S .C., 263-301.
- Zeleny, M. (1981). Multiple criteria decision-making, McGraw-Hill Book Co., New York, N.Y.
- Zeleny, M. (1982) Multiple Criteria Decision Making. McGraw-Hill, New York, 563p.