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A General Overview of Multi-Objective Multiple-Participant Decision Making for Flood Management

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A General Overview of Multi-objective Multiple-participant Decision Making for Flood Management

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ABSTRACT

Decision-making problems in water resources are often associated with multiple objectives and multiple stakeholders. To enable more effective and acceptable decision outcome, it is required that more participation is ensured in the decision making process. This is particularly relevant for flood management problems where the number of stakeholders could be very large. Although application of multi-objective decision-making tools in water resources is very wide, application with the consideration of multiple stakeholders is much more limited. The solution methodologies adapted for multi-objective multi-participant decision problems are generally based on aggregation of decisions obtained for individual decision makers. This approach seems somewhat inadequate when the number of stakeholders is very large, as often is the case in flood management.

The present study has been performed to have an overview of existing solution methodologies for multi-objective decision making approaches in water resources. Decision making by single and multiple stakeholders has been considered under both deterministic and uncertain conditions. It has been found that the use of fuzzy set theory to represent various uncertainties associated with decision making situations under multi-objective multiple-participant environment is very promising. Coupled with multi-objective methods (e. g. compromise programming and goal programming), fuzzy approach has also the ability to support group decisions, to reflect collective opinions and conflicting judgments.

Key Words: Overview; multiple objectives; multiple stakeholders; decision-making; flood management.

1. INTRODUCTION

1.1 General

Water resources planning and management provides decision-tools for: (a) allocation of adequate water to the consumers at appropriate time and place; (b) protection from excessive water (e.g. floodwater); and (c) maintenance of acceptable water quality (Loucks, 1981). The increase in water demand with population growth is applying more stress on available water resources and calls for an efficient and acceptable management of the resources. Also the issue of preserving ecosystems integrity arises in conflict with measures that are taken to meet the population water demand. Major disasters like floods, draughts, intolerable water quality conditions, waterborne disease epidemics etc. trigger consideration of appropriate planning for increased control of water resources. Improved management of water resources requires the planers take decision on: (a) structural measures through appropriate design, construction procedure, removal and operation of control structures; and (b) to implement nonstructural measures through appropriate preparedness, operation and recovery planning.

The water resources decision-making process should also consider different characteristics of water resources systems. The characteristics include those of physical nature of the system (like location, spatial distribution, and dynamic development etc.), as well as reliability and stochastic behavior of the processes within the system. The reduction in availability and, at the same time, growing demand for water give rise to competition among the users for the same resource, resulting in planning for its multipurpose use. The conflict of interest among the multiple users is another main issue that may have different dimensions. Conflicts can be related to functional requirements of different users, like irrigation water demand, municipal water supply demand and hydropower demand etc. Upstream and downstream users may have conflict in the form of both water quality and quantity. The characteristics of the system, in most cases, define the dimension of the conflict that needs to be included in the decision-making process.

1.2 Multi-objective Decision Problems

Water resources planning and management often involves multi-objective decision-making to deal with problems having multiple and conflicting criteria. The objectives can be both quantitative and qualitative. Considering a scenario for construction of a system of dams on a river with objectives e.g., to increase national income, reduce damage due to flood hazard and to minimize adverse environmental impacts etc., there exists considerable difficulty in deciding the best design option as the objectives are not comparable on the same scale and the options that are more likely to achieve one objective may be less effective in obtaining the others. Determination of acceptable relative values for all the objectives is also a difficult task. Multi-objective analysis methods are designed for finding the more preferred alternative solutions to a problem by evaluating the alternatives against the multiple objectives and are widely applied in water resources planning processes (for more details see e.g. Haimes et el., (1975); Loucks et el., (1981); Goodman, (1984) etc.). Cohon and Marks (1975) presented a review and evaluation of multi-objective programming techniques where the approaches are classified into three groups based on three established criteria. Simonovic (1989) used multi-objective technique to develop the Water Resources Master Plan for the Republic of Serbia. Simonovic and Burn (1989) demonstrated that multi-objective technique could be successfully applied in determining the operating horizon for reservoir operation. Hipel (1992) edited the latest developments in multiple objective decision-making techniques, which demonstrate how these methods can be employed to water resources problems.

1.3 Problems Involving Multiple-stakeholders

Multiple-objective decision-making becomes more complicated with the increase in number of individuals/groups involved in the decision making process. In reality, the decision making process often involves multiple decision makers. Policy makers and professional planners are first to name. However, others like NGOs, different interest groups, communities affected by the decision outcomes and general public may be included too. Moving from a single decision maker to a multiple decision maker situation introduces a great deal of complexity into the analysis. The problem is no longer limited to the selection of the most preferred alternative among the non-dominated solutions by an individual. The analysis must also be extended to account for the conflicts among different decision makers with different objectives. In practice, the decision-making in water resources is always associated with multiple decision makers. For example, in order to decide about the flood control measure to be adapted in a floodplain, the decision-making process should include the representatives from all levels of government as well as the residents in the floodplain and other interest groups. It is a real challenge to have a group decision outcome that can satisfy all the stakeholders (Arrow, 1963). Group decision making under multiple objectives involves a diverse and interconnected fields like preference analysis, utility theory, social choice theory, voting, game theory, expert evaluation analysis, aggregation, economic equilibrium theory and so on (Hwang and Lin, 1997).

1.4 Uncertainties in Decision Making Problems

Water resources decision-making is always associated with some degree of uncertainty. This uncertainty could be categorized into two basic types: uncertainty caused by inherent hydrologic variability and uncertainty due to a lack of knowledge (Simonovic, 2000). Uncertainty of the first type is associated with the spatial and temporal changes of hydrologic variables like flow, precipitation, water quality etc. The second type of uncertainty occurs when the particular value of interest cannot be assessed exactly because of the limitation in the available knowledge. For example, the decision for operating a dam is associated with uncertainties of both types. The decision maker has to consider the uncertainty in river flow, as well as the uncertainties associated with potential dam failure and/or possible social implications of excess and shortage of water.

Most of the water resources decision making in the real world takes place in a situation where the goals, the constraints and the consequences of the possible actions are not known precisely (Bellman and Zadeh, 1970). Controversy or ambiguity in comparing and weighing objectives can create decision uncertainty. The uncertainty is also present in the selection of an index to measure risk, which should be technically correct as well as measurable and meaningful. The quantification of social values is another source of uncertainty. Even when a risk measure and the cost of risk are generated, the risk communication and acceptance levels still remain uncertain, as they depend on risk perception by the affected public. Without information on the uncertainties for various possible outcomes, decision makers may make less than optimal decisions (Morgan and Henrion, 1990). Without adequate uncertainty analysis, prioritization of additional research intended to reduce uncertainty cannot occur. This reduces the utility of the model output for management.

Uncertainties in water resources decision-making have been analyzed from several different perspectives. Borsuk et al. (2001) adapted a probabilistic model (Probability Network model) to support decision in the near term under uncertainties associated with physical parameters. The use of fuzzy set theory (Zadeh, 1965) has become increasingly popular in addressing imprecision, uncertainty and vagueness in group-decision making. Kacprzyk and Nurmi, (1998) presented the solution of a group decision making problem under individual fuzzy preference relations and a fuzzy majority. Bender and Simonovic (2000) used fuzzy compromise programming to water resources systems planning under uncertainty. Kwok et al. (2001) represented the uncertainty in relative importance of objectives by the qualitative judgments on pairs of objectives. Also fuzzy linguistic terms have been used to address the subjective judgment of the decision makers while stating the preference for the alternatives.

1.5 Present Study

To deal with complex water resources decision problems, like flood management, it is necessary to develop a tool, which would consider multiple stakeholders with multiple objectives where uncertainties exist at different stages of the decision-making process. Flood management comprises of different water resources activities aimed at reducing potential harmful impact of floods on people, environment and economy of a region. Sustainable floodplain management requires empowerment of stakeholders, adjustment to the environment, and integrated consideration of economic, ecological and social consequences of disastrous flood. The flood management process in Canada, (as elaborated for the Red River basin by Simonovic, 1999), has three major stages: (a) planning; (b) flood emergency management; and (c) post-flood recovery. Appropriate decision-making in each of these stages is very important to establish an efficient flood management process. During the planning stage, different alternative measures (both structural and non-structural) are analyzed and compared for possible implementation in order to minimize future flood damage. Flood emergency management includes regular evaluation of the current flood situation and daily operation of flood control works. The evaluation process includes identification of potential events that could affect the current flood situation (such as dike breaches, wind set-up, heavy rainfall etc.) and identification of corresponding solution measures for flood fighting (including building temporary structures or upgrading existing ones). Also, from the evaluation of current situation, decisions are made regarding evacuation and re-population of different areas. Post-flood recovery involves numerous decisions regarding return to normal life. Main issues during this stage include assessment and rehabilitation of flood damage, and provision of flood assistance to flood victims. In all these three stages, the decision making process takes place in a multi-disciplinary and multi-participatory environment, where analyses must involve tradeoffs among multiple non-commensurable criteria.

During and after the devastating flood of 1997 in the Red River basin it has been indicated that many of the stakeholders in the basin, particularly the flood plain residents, did not have adequate involvement in the flood management decision-making. Dissatisfaction among the stakeholders about emergency management decisions, including evacuation, was particularly high. To resolve the issue it is necessary that the views of the stakeholders be included in a decision making process that will be well accepted to all those involved.

A number of solution approaches at present are available for multi-objective multi-participant decision problems. Most of them are based on the technique to solve the decision problem for an individual stakeholder at the time and subsequently aggregate the results for all. The method has potential deficiency for application when the number of decision makers is large. Also, individuals usually compare the alternatives from different standpoints, and so it may prove infeasible to aggregate their preferences.

The objective of this study is to investigate existing methods for solving multi-objective multiple stakeholder decision-making problems, and to analyze the applicability of the methods to flood management. The summary of decision-making approaches reflects the potential value of existing research in multiple-objective multiple-stakeholder water resources decision-making under uncertainty. Although methodologies exist for incorporating multiple stakeholders in the decision-making process, for very large number of stakeholders, as often required in flood management, the methodologies seem inadequate.

In the following section a general formulation of a multiple-objective multiple-participant problem with general requirements for its solution are presented. The next section contains a classification of existing solution approaches for multi-objective problems followed by the summary of a few works on multi-objective multiple-participant problems. The classification of approaches is provided for: multi-objective problems with single and multiple decision makers under both deterministic and uncertain conditions.

2. GENERAL FORMULATION OF MULTI-OBJECTIVE MULTIPLE-PARTICIPANT DECISION PROBLEM

Formulation of a multi-objective multiple-participant decision problem is based on the following basic components:

1. A set of potential alternatives;
2. A set of objectives or criteria;
3. A number of decision makers;
4. A preference structure or weights; and
5. A set of performance evaluations of alternatives for each objective or criteria.

A multi-objective problem is characterized by a p-dimensional vector of objective functions. In mathematical terms, this can be formulated as:

$$Z(x) = [Z_1(x), Z_2(x), ..., Z_p(x)] \qquad .... \quad (1)$$

subject to

$$x \in X \qquad .... \quad (2)$$

where X is a feasible region.

$$X = \{x : x \in R^n, g_i(x) \leq 0, x_j \geq 0 \forall i, j\} \qquad .... \quad (3)$$

where R = set of real numbers; $g_i(x)$ = set of constraints; and x = set of decision variables.

Every feasible solution to the problem (Eq.(1)), i.e. all $x \in X$, implies a value for each objective, i.e., $Z_k(x)$, $k = 1, \ldots p$. The p-dimensional objective function maps the feasible region in decision space X into the feasible region in objective space $Z(x)$, defined on the p-dimensional vector space.

In general, one cannot optimize a vector of objective functions (Haimes and Hall, 1974). In order to find an optimal solution, it is required that information about preferences are available. Without this information the objectives are incommensurable and therefore incomparable implying that optimum solution could not be achieved since all feasible solutions are not ordered (comparable). A complete ordering can be obtained in this case only by introducing value judgments into the decision making process.

In the first step of the multi-objective analysis problem, a set of nondominated or 'noninferior' solutions is sought within the feasible region instead of seeking a single optimal solution. The nondominated solutions are the conceptual equivalents in multi-objective problems to a single optimal solution in a single-objective problem. For each of the solutions outside the nondominated set, there is a nondominated solution for which all objective functions are unchanged or improved and there is at least one, which is strictly improved. For a set of feasible solutions X, the set of nondominated solutions, denoted as S, is defined as follows:

$S = \{x : x \in X\}$, $x' \in X$ such that $Z_q(x') > Z_q(x)$

for some $q \in \{1,2,....., p\}$ and $Z_k(x') \geq Z_k$ for all $k \neq q$ } ……… (4)

Each nondominated solution $x \in S$ implies values for each of the p objectives *Z(x)*. The collection of all the *Z(x)* for $x \in S$ yields the nondominated set *Z(S)*. The nondominated solution is defined in the objective space, and it is a subset of the feasible region in the objective space, i.e. $Z(S) \subseteq Z(X)$. From the definition of S it is obvious that if one objective function improves by moving from one nondominated solution to another, then one or more of the other objective functions must decrease in value.

Multi-objective programming problems can be continuous or discrete. Continuous formulation requires analytical description of the objective function vector. One example of the continuous formulation is a linear multi-objective problem where:

1. All the objective functions are linear, that is, for *i* = 1, …*i*

$$f_i(x) = c_{i1}x_1 + c_{i2}x_2 + ... + c_{in}x_n \qquad ……… \quad (5)$$

where the c_{i1} , c_{i2} ….., c_{in} are given constants.

2. All constraints are described by linear inequalities of the form

$$a_{j1}x_1 + a_{j2}x_2 + ... + a_{jn}x_n \begin{array}{c} \leq \\ = \\ \geq \end{array} b_j \qquad ……… \quad (6)$$

where the a_{j1}, a_{j2} ….., and b_j are given constants.

A problem is called discrete if the feasible set X contains only finite number of points. For example, if the decision maker can only choose from a finite number of alternatives, then X is necessarily finite and the problem is discrete.

Consider a problem where m alternatives are to be evaluated by n decision makers, who are using p objectives. The general conceptual decision matrix for this discrete multi-objective multi-participant problem is shown in Table 1.

Table 1: Conceptual decision matrix for a discrete multi-objective multi-participant decision problem

	O_1	…	O_p
A_1	a_{11}	…	a_{1p}
…	…	…	…
A_m	a_{m1}	…	a_{mp}
DM_1	w_{11}	…	w_{p1}
…	…	…	…
DM_n	w_n	…	w_{pn}

In Table 1, A denotes the alternative, O is the objective and DM is the decision maker. The preference of the decision maker k (k = 1 …..n) for the objective j (j = 1….p) is expressed by w_{jk} and a_{ij} is the performance evaluation of the alternative i (i = 1…..m) for each objective j. The objectives as well as the performance evaluations can either be quantitative or qualitative.

The classical outcome of the decision matrix is the ranking of the alternatives. To obtain that, a number of steps are necessary like establishing the preference structure, the weights and also the performance evaluations. Among the multi-objective methods, some perform the ranking, some establish the preference structure, and some methods come up with the values inside the matrix. Some methods have the ability to incorporate qualitative data into the analysis. And some methods are capable of including multiple decision makers in the decision making process.

In the following a general mathematical formulation of this multi-objective multi-participant problem is presented followed by a general description on the solution approach (Hwang and Lin, 1987). A payoff matrix can be obtained for the problem where m alternatives are to be evaluated by n decision makers, who are using p objectives:

$$A^k = [a_{ij}]^k = \begin{bmatrix} a_{11} & .. & .. & a_{1p} \\ a_{21} & .. & .. & a_{2p} \\ .. & .. & .. & .. \\ a_{m1} & .. & .. & a_{mp} \end{bmatrix}, (k = 1,\ldots\ldots n) \qquad \ldots\ldots\ldots \qquad (7)$$

Here $A^k_{i.} = [a_{i1} \ldots\ldots a_{ip}]^k$ means that alternatives i are being evaluated by objectives from 1 to p

by decision maker k. The symbol $A^k_{.j} = [a_{1j} \ldots\ldots a_{mj}]^k$ means that the objective j is being used by decision maker k to evaluate all alternatives from 1 to m.

The solution to this problem is to have each alternative be evaluated by all the decision makers using all objectives. The process can be summarized as the following mapping function (Ψ):

$$\Psi : \{A^k \mid k = 1, \ldots\ldots n\} \rightarrow \{G\} \qquad \ldots\ldots\ldots \qquad (8)$$

where G is a collective weighted agreement matrix.

It is crucial that this mapping function represent all objectives that the decision makers use in judging all the alternatives. Elements of the mapping function can be obtained using either the Ordinal (Cook and Seiford, 1978 among others) or the Cardinal (Souder, 1972; Keeney and Kirkwood, 1975 and others) approach. These are used to evaluate the alternatives through ranking and scoring respectively.

2.1 The Ordinal Approach

The matrix presented in equation (6) includes all objectives used in ranking the alternatives by all decision makers. The alternatives can be achieved by two approaches – the agreed criteria approach and the individual approach.

2.1.1 Agreed Criteria Approach

The agreed criteria approach involves each decision maker using the same objective to find the matrices of all alternatives, the decision makers being in agreement on the type of objectives used. For each objective j ($j = 1 \ldots\ldots p$) the following matrix can be obtained:

$$C = \begin{bmatrix} a_{1j}^1 & a_{1j}^2 & . & . & a_{1j}^n \\ a_{2j}^1 & a_{2j}^2 & . & . & a_{2j}^n \\ . & . & . & . & . \\ . & . & . & . & . \\ a_{mj}^1 & a_{mj}^2 & . & . & a_{mj}^n \end{bmatrix} \quad (j = 1, \ldots..p) \qquad \ldots\ldots\ldots \qquad (9)$$

The score is then determined for each alternative by each decision maker. The alternatives are ranked according to the sum of all scores giving the first place to the alternative having the highest score.

Then a collective ordered matrix is achieved by mapping:

$$\{A^k\} \rightarrow \{A'\} \qquad \ldots\ldots\ldots \qquad (10)$$

where $k = 1, \ldots\ldots, n$.

That is:

$$A' = [a'_{ij}] = \begin{bmatrix} a'_{11} & a'_{12} & . & . & a'_{1p} \\ a'_{21} & a'_{22} & . & . & a'_{2p} \\ . & . & . & . & . \\ . & . & . & . & . \\ a'_{m1} & a'_{m2} & . & . & a'_{mp} \end{bmatrix} \; (i=1,\ldots,m;\, j=1,\ldots,p) \qquad \ldots\ldots\ldots \quad (11)$$

Here, a'_{ij} is the ordering of alternative i under objective j. If the decision maker wants to place weights on the objectives, the vector of weights is expressed as $\boldsymbol{w} = (w_1, \ldots\ldots. w_p)$, where w_j is the weight assigned with the j th objective and $\sum_{j=1}^{p} w_j = 1$.

Then an agreement matrix (π) is formulated, this is a square nonnegative matrix in which entries π_{ilj} represent the number of orderings where the ith alternative is placed in the lth position for a given objective j. The set of weights for objectives should be used in the decision process resulting in the collective weighted matrix:

$$G = [g_{ij}] = \sum_{j=1}^{p} \pi_{ilj}\, w_j \qquad \ldots\ldots\ldots \quad (12)$$

where

$$\pi_{ilj} = \begin{cases} 1 & if\ ithalternativeis\ placedin\ jthposition \\ 0 & otherwise \end{cases} \qquad \ldots\ldots\ldots \quad (13)$$

Alternative i is matched with rank number l so that the sum of the corresponding assigned weight values is the largest possible. This can be achieved by solving the so-called assignment problem of linear programming:

$$\text{Max } \sum_{i=1}^{m}\sum_{l=1}^{m} g_{ij} x_{il} \qquad \ldots\ldots\ldots \quad (14)$$

Subject to

$$\sum_{i=1}^{m} x_{il} = 1 \text{ , } l = 1 \ldots\ldots m \qquad \ldots\ldots\ldots \quad (15)$$

$$\sum_{l=1}^{m} x_{il} = 1 \text{ , } i = 1 \ldots\ldots m \qquad \ldots\ldots\ldots \quad (16)$$

where

$$\pi_{il} = \begin{cases} 1 & iflhasbeenassignedtoi \\ 0 & otherwise \end{cases} \qquad \ldots\ldots\ldots \quad (17)$$

2.1.2 Individual Approach

The individual approach involves each decision maker having his/her own objective, which may or may not differ from others, to determine matrix for each alternative. The decision maker may assign a set of weights to the objective, $\boldsymbol{w} = (w_1, \ldots\ldots w_p)^k$, $k = 1, \ldots\ldots n$ and $\sum_{j=1}^{p} w_j^k = 1$, where w_j^k is the weight assigned to the jth objective by individual k. Then the decision maker sets up his/her own agreement matrix in the same manner as described in the previous section. The inclusion of weight to objectives allows the setting up of an assignment problem to get the linear ordering of alternatives for each decision maker:

$$F^k = [\, f_{ij}^{\,k} \,] = [\sum_{j=1}^{p} \pi_{ilj}\ w_j]^k \qquad \ldots\ldots\ldots \quad (18)$$

followed by the formulation of the assignment problem of linear programming for each decision maker:

$$\text{Max} \sum_{i=1}^{m} \sum_{l=1}^{m} f_{ij}^{\,k} x_{il} \qquad \ldots\ldots\ldots \quad (19)$$

Subject to

$$\sum_{i=1}^{m} x_{il} = 1 \ , \ l = 1, \ldots\ldots m \qquad \ldots\ldots\ldots \quad (20)$$

$$\sum_{l=1}^{m} x_{il} = 1 \ , \ i = 1, \ldots\ldots m \qquad \ldots\ldots\ldots \quad (21)$$

where

$$\pi_{il} = \begin{cases} 1 & if l has been assigned to i \\ 0 & otherwise \end{cases} \qquad \ldots\ldots\ldots \quad (22)$$

In each set of preference ordering of the alternatives, scores are given to first-ranked to last ranked for each decision maker. Then the sum of the individual scores for each alternative is determined. The alternative with the highest score is placed in the first place and in this way the complete ordering of alternatives is obtained.

2.2 The Cardinal Approach

The cardinal approach is followed when the different objectives have different types, units or scales. Two stages are required to transform these objectives into a set of comparable scales. First, the qualitative terms are transferred into an interval scale. The decision makers should agree on the scaling procedure they use. Secondly, the values with different units are normalized. Vector normalization can be used because all objectives are measured in dimensionless units. This procedure implies that each column vector of the individual decision matrix is divided by its norm, so that each normalized value d_{ij}^k of the individual normalized decision matrix D^k can be calculated as

$$d_{ij}^{k} = \frac{a_{ij}^{k}}{\sqrt{\sum_{i=1}^{m} (a_{ij}^{k})^2}} \qquad \ldots\ldots\ldots \quad (23)$$

where, $i = 1, \ldots\ldots m$ is the number of alternatives; $j = 1,\ldots\ldots p$ is the number of objectives and $k = 1, \ldots\ldots n$ is the number of decision makers. The comparison of matrices includes all alternatives, all objectives and all evaluations by the decision makers. Now the formulation of collective ordering can be found again using the agreed criteria and the individual approach.

In the agreed criteria approach, all decision makers have equal role, and their evaluations have equal importance. Under a given objective, a collective value is found which is the aggregation of the values of the decision makers. The collective matrix can be written as:

$$C = [c_{ij}] = [\frac{\sum_{k=1}^{n} d_{ij}^{k}}{n}] \quad i = 1, \ldots\ldots m \, ; j = 1, \ldots\ldots p \qquad \ldots\ldots\ldots \quad (24)$$

Since all objectives may or may not be of equal importance, a vector of weights from the decision makers is set up, given by $\boldsymbol{w} = \{w_1,\ldots\ldots\ldots\ldots w_p\}$, $\sum_{j=1}^{p} w_j = 1$. Now the weighted normalized matrix can be calculated by multiplying each column of the matrix C with its associated weight w_j. Therefore, the weighted normalized matrix, F is

$$F = [f_{ij}] = [c_{ij} w_j] \ , i = 1, \ldots\ldots m \ ; \ j = 1, \ldots\ldots p \qquad \ldots\ldots\ldots \quad (25)$$

In the individual approach, decision maker k has a personal preference set of objectives $(1,\ldots\ldots p)^k$ which may or may not share some of the other decision maker's objectives. An individual has to assign a vector of objective weights as $w^k = (w_1^k, \ldots\ w_p^k)$, $k = 1, \ldots\ldots n$ and $\sum_{j=1}^{p} w_j^k = 1$, where w_j^k is the weight assigned to the j objective by individual k.

The individual weighted normalized matrix, F^k, can be calculated by multiplying each column of the matrix D^k with its associated weight w_j^k. Therefore, the individual weighted normalized matrix, F^k, is

$$F^k = [\, f_{ij}^k \,] = [\, w_j^k \, d_{ij}^k \,] \,, \ (k = 1, \ldots n \,;\ i = 1, \ldots m \,;\ j = 1, \ldots p) \qquad \ldots\ldots\ldots \quad (26)$$

The methods to find the collective preference ordering are same as that described for ordinal approach. The alternatives are ranked according to their highest score.

2.3 Flood Control Decision Making

The formulation illustrated in this section is applicable for any water resources planning problem. Our particular interest is in flood-control decision making. Experience with flood management in the Red River Basin (Simonovic, 1999; IJC, 2000; Simonovic and Carson, 2002) will be used in this paper. One of the flood management problems in the Red River basin is the complex large-scale problem of ranking flood control alternatives. During the evaluation of the alternatives it is necessary to consider multiple objectives that may be either quantitative or qualitative. The flood management process in the basin also involves numerous stakeholders in both Canada and the USA. They are different levels of government, different agencies, private organizations, interest groups and general public. They all have different and specific needs and responsibilities during all the stages of flood management – planning, emergency management and flood recovery period.

After the devastating flood in the Red River in 1997, different alternatives have been assessed to alleviate the future impact of flooding events in the flood plain area. Winnipeg with approximately 670,000 people is the biggest community located in the flood plain. Two measures are primarily considered to be capable of providing the large-scale improvement in reliability that is required for the protection of the city from future floods. Those are – expansion of the Red River Floodway and construction of Ste. Agathe Detention Structure. There are advantages of all the alternatives in achieving different economic, environmental, physical and social objectives.

Currently, the provincial government is responsible for the decision making about the flood control measures. The decision making process involves consulting different organizations for their technical input. Concerns of general stakeholders about the alternatives are gathered through public hearings and workshops. Economic analysis plays an important role in formulating plans for reducing flood damages and making operational decisions during the emergency. One of the main limitations of the existing flood management methodology is the consideration of mostly the economic aspects. Very minor attention is given to environmental and social impacts of floods.

Successful floodplain planning and management, including flood preparation and mitigation, require reliable, accurate, compatible and accessible data. IJC (2000) reported that fragmented and incomplete data and information are the major obstacles to better flood planning and management in the Red River valley. Different types of data required for a flood management process include technical data, economic data and also flood related data about impacts and consequences of a flooding event. Topographic, hydrological, hydrometric and climatological data are among the technical ones, which are required for the analysis of future flood control measures and for the operation of existing flood control structures, and also for the evaluation of different hydrologic scenarios. Cost-benefit analysis plays very important role in assessing the credibility of an alternative. Inclusion of social science research, specifically inclusion of information about risk perception and values, would make the decision making process more explicit to be applied for flood management.

There has been increasing concern of general public about the decisions to be taken on the flood control measures. During the 1997 flood, it has been indicated that, certain stakeholders of the basin, particularly the flood plain residents, did not have adequate involvement in flood management decision-making. Dissatisfaction has been observed among the stakeholders about other emergency management decisions including evacuation. The view of all these stakeholders is also necessary to be analyzed to offer a decision support system that will be well accepted to all who are involved.

Decision-making for flood management is often affected by uncertainties in information on which the decision is based. The uncertainties may arise from mainly two sources: (a) uncertainties in approximation and description of physical processes (precipitation, flow, water quality etc.); and (b) uncertainties in assessing particular values of interest to the decision maker. Probabilistic approaches are widely used by scientists and engineers to address the uncertainties of the first category. Developed stochastic programming methods in this category deal with at least three sources of errors: (1) variations in the estimation of parameters associated with probability distributions governing the random variables of interest; (2) variations in data at different time instants as the development and implementation of the optimal decision rules take place; and (3) the presence of uncertainty as to the type of probability distribution available with associated data (Goicoechea, 1982). The second type of decision uncertainties is more profound in the arena of public decision-making like in the case of flood management. The goals, the constraints and the consequences of possible actions in flood management are practically not known precisely. This imparts subjectivity in the decision making process where the relative strengths and weaknesses of different alternatives are evaluated by relating their impacts to a number of evaluation criteria or objectives. It is therefore difficult to compare and assign appropriate weights to different non-commensurate objectives that may range, for example, from flood damage in monetary units to psychosocial impacts of flood on one part of population living in the floodplain. Quantification of social values and impacts is another source of uncertainty. It is necessary to address all these uncertainties properly in order to make a decision support tool more effective for flood management. Fuzzy set theory has been applied by many researchers to capture the subjective uncertainties in the decision making process, but a proper methodology to address the uncertainties inherent in a real world flood management situation is yet to be developed.

There is a very strong and growing demand as shown in the Red River example for developing a method to incorporate all stakeholders in the decision-making. A common approach is to solve the decision matrix, shown before, for each individual and then aggregate the results for all the individuals. This method does not seem to be appropriate when the number of stakeholders in the decision making process is very large. Process of finding the preference structure for different objectives for multiple decision makers needs attention too. Individuals usually compare the alternatives from different standpoints, and it may prove infeasible to aggregate their preferences. Keeping all these issues in mind a methodology for multi-objective decision aid is needed to be introduced, where the compromise between socio-economic and technical points should exist. The method should reflect the active participation of all the stakeholders, and the uncertainties inherent in the decision making process should be addressed properly. The tool should be able to aid in flood management decision-making. Available data from the Red River basin can be used to test the methodology.

3. CLASSIFICATION OF SOLUTION APPROACHES FOR MULTI-OBJECTIVE PROBLEMS

The classification and comparison of the approaches to deal with multi-objective problems have been made several times e.g., by Cohon and Marks (1975), Nachtnebel (1994), Duckstein and Szidarovszky (1994), Fuller and Carlson (1996), Martel (1999) and many others. These classifications are based on the criteria that fit the respective authors research interests. In this section we will review the general methods for multiple-objective decision making with single, as well as multiple decision makers, in both deterministic and uncertain conditions.

3.1 Deterministic Multiple-Objective Problem – single decision maker

Cohon and Marks(1975) established three criteria for the evaluation of the multi-objective solution techniques. These are - the computational efficiency, explicitness of trade offs among objectives and the amount of information generated for decision-making. Based on these criteria they classified the multi-objective approaches into three groups: (i) methods for generating the nondominated set; (ii) methods with prior articulation of preferences; and (iii) methods with progressive articulation of preferences.

3.1.1 Methods for Generating the Nondominated Set

In these methods a vector of objective functions is considered to identify and generate the subset of nondominated solutions in the feasible region. These methods deal only with the physical realities of the problem, i.e. the constraints, and in doing so, make no attempt to consider the preferences of a decision maker. The outcome of these methods, the nondominated solutions, help the decision makers gain insight in the physical reality of the problem.

Among the several methods available to generate the set of nondominated solutions, four are widely recognized. These are: Weighing method; ε-constraint method; Philip's linear multi-objective method; and Zeleny's linear multi-objective method.

Weighing and *ε-constraint methods* transform the multi-objective problem into single objective format, and then the set of nondominated solutions can be generated by parametric variation of the weights and ε-parameter.

The *weighing method* states that non-dominated solutions can be obtained by solving a scalar optimization problem, in which the objective function is a weighted sum of the components of the original vector-valued objective function *Z(x)*. That is, the solution to the following problem is in general nondominated:

$$\max \sum_{k=1}^{p} w_k Z_k(x) \qquad \ldots\ldots\ldots \quad (27)$$

subject to

$$x \in X \qquad \ldots\ldots\ldots \quad (28)$$

where $w_k \geq 0$ for all k and strictly positive for at least one objective. The nondominated set and the set of nondominated solutions can be generated by parametrically varying the weights w_k in the objective function.

In the ε-*constraint method*, nondominated solutions can be found by solving

$$\max Z_r(x) \qquad \ldots\ldots\ldots \quad (29)$$

subject to

$$x \in X \qquad \ldots\ldots\ldots \quad (30)$$

$$Z_k(x) \geq \varepsilon \quad \text{all } k \neq r \qquad \ldots\ldots\ldots \quad (31)$$

in which ε is a lower bound of objective k. Parametric variation of ε in Eq.(31) traces out the nondominated set.

The other two methods (Philip's and Zeleny's linear multi-objective problems) do not require the transformation of the problem into a single objective format and operate directly on the vector of objectives to obtain the nondominated solutions. Both methods are applicable for linear problems only.

3.1.2 Methods with Prior Articulation of Preferences

The generating techniques mentioned in (3.1.1) are based on incomplete orderings associated with the p objectives of the original multi-objective problem. The methods in this class are based on the idea of deriving a complete or more complete ordering to eliminate some or most of the noninferior solutions. The basis for the orderings is the articulation of preferences prior to the solution of the multi-objective problem. Methods in this class are further divided into continuous and discrete types.

<u>Continuous</u>

After generating the set of nondominated solutions, the task of the decision maker is to select one of those solutions as his/her final choice. Then this solution is one that meets the physical constraints and satisfies the value structure of the decision maker. This group of methods requires that the decision maker articulates his/her preference structure regarding the objective functions in search for the solution. These preferences are then built into the formulation of the mathematical model of the multi-objective problem. Following are the three examples of techniques with prior articulation of preferences.

Goal programming (Charnes and Cooper, 1961) is based on the minimization of the weighted absolute deviations from targets for each objective. For the general vector maximization problem, the goal programming formulation is:

$$min\sum_{k=1}^{p}\left|d_k\right| \quad \ldots\ldots\ldots \quad (32)$$

subject to

$$x \in X \quad \ldots\ldots\ldots \quad (33)$$

$$Z_k(x) - d_k = T_k \qquad k = 1,\ldots p \quad \ldots\ldots\ldots \quad (34)$$

where d_k is the deviation from the target for the kth objective and T_k is the target for the kth objective.

In the *Utility function assessment* method (Keeney and Raiffa, 1993) the preference structure of the decision maker is formally and mathematically represented by a utility function. In the presence of a vector of objectives, it is assumed that all information pertaining to the various levels of the objectives can be captured by an individual's value function (in the deterministic case) and utility function (in the probabilistic case). Geoffrion (1967) developed a method for proceeding more or less directly from a specification of a utility function to the best-compromise solution, bypassing the generation of the nondominated set in most cases. For a two objective problem, the formulation is:

$$\max U[Z_1(x), Z_2(x)] \quad \ldots\ldots\ldots \quad (35)$$

subject to

$$x \in X \quad \cdots\cdots\cdots \quad (36)$$

Where U is a monotonically nondecreasing ordinal function (in each objective). Figure 1 illustrated the application of the utility function approach. A compromise solution, A is reached at the point where the utility function touches the feasible region.

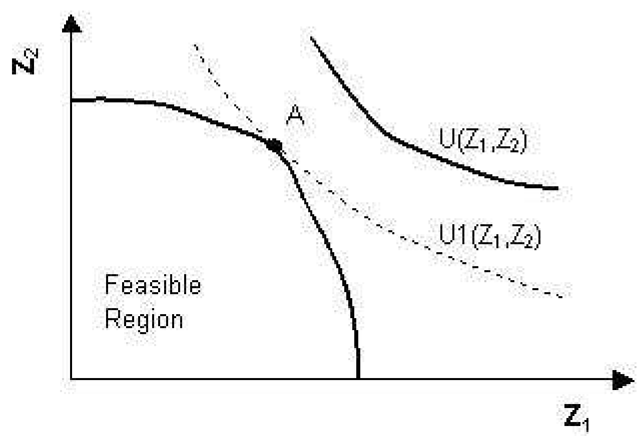

Figure 1: Illustration of the utility function approach

Haimes and Hall (1974) presented *surrogate worth trade-off method* with the motivation that the choice of optimal weights should be made with the knowledge that trades-offs are a function of the levels of objectives. These trade-off functions show the relationship between a weight on one objective and the value of that objective. A set of trade-off functions may be interpreted as a disaggregated non-inferior set, in which the objectives are considered in pairs.

Discrete

These methods are for the situations in which the decision makers must choose from a finite number of alternatives which are evaluated on a common set of non-commensurable multiple objectives or criteria. These sort of problems occur in many practical situations. The methods in this group range from the very simple to the very complex. Some of the methods are: Exclusionary screening; Conjunctive ranking; Simple additive weighing (SAW) method; ELECTRE I and II; Indifference tradeoff method; Direct- rating method; AHP etc.

For example, in the classical *simple additive weighing (SAW) method* (Hwang and Yoon, 1981), the decision maker assigns a set of weights, $\boldsymbol{w} = (w_1, w_2, \ldots\ldots., w_n)$, to the objectives, x_j, $j = 1,\ldots n$. Then the performance of alternative A_i, is calculated as:

$$U_i = \sum_{j=1}^{n} w_j r_{ij} \Big/ \sum_{j=1}^{n} w_j \qquad \ldots\ldots\ldots \quad (37)$$

where, r_{ij} is the rating of the ith objective under the jth objective with a numerically comparable scale. This is the simplest form of Multiple Attribute Utility Theory (MAUT). The most preferred alternative, A^*, is then selected such that:

$$A^* = \{A_i \mid \max_i U_i\} \qquad \ldots\ldots\ldots \quad (38)$$

The Analytic Hierarchy Process (AHP) (Saaty, 1980) is a flexible decision making process to help people set priorities and make the best decision when both qualitative and quantitative aspects of a decision need to be considered. The AHP engages decision makers in breaking down a decision into smaller parts, proceeding from the objective to criteria to subcriteria down to the alternative courses of action. Decision makers then make simple pairwise comparison judgments throughout the hierarchy to arrive at overall priorities for the alternatives.

3.1.3 Methods with Progressive Articulation of Preferences

The methods of this class generally follow an algorithmic approach which can be stated as (1) identification of a nondominated solution, (2) seeking the tradeoff information of the decision maker regarding this solution and modification of the problem accordingly, and (3) repetition of (1) and (2) until the decision maker expresses the acceptance for a current achievement level, provided one exists. These methods typically require greater involvement of the decision maker. This process may be advantageous as the decision maker gains greater understanding of the problem, but in the other hand has disadvantage of being time consuming. Some methods of progressive articulation of preferences are: Compromise programming; Step method (stem); Method of Geoffrion; SEMOPS method; TRADE method; etc.

Compromise programming method (common in water resources management) identifies the solution, which is closest to the ideal solution by minimizing the distance from the 'ideal' point to the solution selected (Zeleny, 1973). The distance measure used in compromise programming is the set of D metrics defined for the two-objective problem as:

$$D_r(x) = \left[\left(w_1^{\,r} \left| \frac{f_1^o - f_1(x)}{f_1^o - f_1^w} \right|^r \right) + \left(w_2^{\,r} \left| \frac{f_2^o - f_2(x)}{f_2^o - f_2^w} \right|^r \right) \right] \quad \ldots\ldots\ldots \quad (39)$$

where D_r = distance from the ideal point; w_i weights; f_i^0 = optimal value for objective i; f_i^w = worst value obtained for objective i; $f_i(x)$ = result of implementing decision x with respect to the ith objective; and r = parameter with $1 \le r \le \propto$.

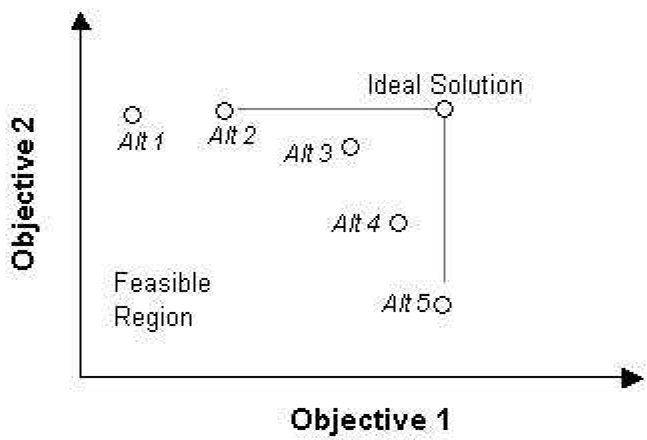

Figure 2: Illustration of the Compromise programming method

The compromise set is simply the set of all compromise solutions obtained by the minimization of D_r for a given set of weights w_i and for all $1 \le r \le \propto$ (usually the values for r considered are r = 1, 2, and $\propto$). Thus Compromise programming is allows expression of the decision maker's preference in two ways - the parameter r reflects the importance of the maximal deviation from the ideal point and the weights reflect the relative importance of each objective. Figure 2 shows the graphical representation of the Compromise programming method.

3.2 Multiple Objective Problem Under Uncertainty – Single Decision Maker

In most of the real world problems, some of the decision data (a_{mp} and w_{pm}) shown in Table 1 can be precisely assessed while others cannot. Both probabilistic and fuzzy set approaches are used to denote these uncertainties. Probabilistic approaches follow two main steps, 1) determining the probability of occurrence of an event; and 2) translating that probability into an evaluation of risk by determining the consequence of the event occurring or not occurring. PROTRADE method can be named that uses probabilistic approach to deal with uncertainty in multi-objective problem (Goicoechea et al., 1982).

The use of fuzzy set theory is more common and allows incorporating un-quantifiable, incomplete and non-obtainable information, and partially ignorant facts into the decision model. Introduced by Zadeh (1965), fuzzy logic and fuzzy set theory have been used for modeling ambiguity and uncertainty in the decision-making. Fuzzy sets are a generalization of conventional set theory that was introduced as a mathematical way to represent vagueness of parameters. The basic idea in fuzzy logic is that statements are not just 'true' or 'false', but partial truth is also accepted. In the same way, in fuzzy set theory, partial belonging to a set, called a fuzzy set, is possible. Fuzzy sets are characterized by membership functions. By definition, if X is a collection of objects denoted generically by x, then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \,|\, x \in X\} \qquad \ldots\ldots\ldots \quad (40)$$

$\mu_{\tilde{A}}(x)$ is called the membership function or grade of membership of x in $\tilde{A}$. These membership functions are appropriate for modeling preferences of the decision maker. Despic and Simonovic (2000) have developed an approach for deriving the membership functions for flood management.

Fuzzy decision-making was first introduced by Bellman and Zadeh (1970). According to them, if goals G_i and the constraints B_j are fuzzy and are characterized by membership functions $[\mu_{G_i}(x), \mu_{B_j}(x)]$, then the decision space can be defined through their fuzzy intersection operation (shown in Figure 3):

$$\mu_z(x) = \mu_{G_i}(x) \cap \mu_{B_j}(x) \qquad \text{.........} \quad (41)$$

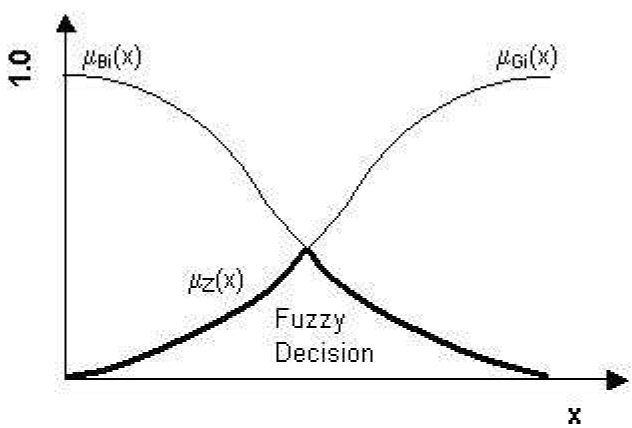

Figure 3: Illustration of fuzzy decision

Fuzzy theory has been applied in multi-objective decision making for 1) the aggregation of performance ratings with respect to all objectives for each alternative; and 2) the rank ordering of alternatives according to the aggregated score. Incorporation of uncertainty in various multi-objective methods by applying fuzzy theory has been done by various authors. Zimmerman (1987) and Chen and Hwang (1992) contain a very good summary of these methods.

To demonstrate Simple additive weighing (SAW) method, let both w_j and r_{ij} be fuzzy sets defined as:

$$w_j = \{(y_j, \mu_{w_j}(y_j))\}, \quad \forall\, j \quad \text{and} \qquad \dots\dots\dots \quad (42)$$

$$r_{ij} = \{(x_{ij}, \mu_{r_{ij}}(x_{ij}))\}, \quad \forall\, i, j \qquad \dots\dots\dots \quad (43)$$

where y_j and x_{ij} take their numbers on the real line and, $\mathbb{R}$ $\mu_{w_j}(y_j)$ and $\mu_{r_{ij}}(x_{ij})$ take values in [0,1]. Then the utility of alternative A_i can be calculated as:

$$U_i = \{(u_i, \mu_{U_i}(u_i))\} \qquad \dots\dots\dots \quad (44)$$

The variable u_i takes its value on the real line $\mathbb{R}$ and can be obtained using

$$u_i = \sum_{j=1}^{n} y_j x_{ij} \Big/ \sum_{j=1}^{n} y_j \qquad \dots\dots\dots \quad (45)$$

Use of fuzzy compromise programming has been introduced in water resources decision making by Bender and Simonovic (2000), where the distance matrix (shown in equation (39)) has been transformed to a fuzzy set by changing all input from crisp to fuzzy and applying the fuzzy extension principle. Fuzzification of objective values, objective weights, and the distance matrix exponent has been done to incorporate subjective uncertainties while ranking the alternatives.

Fuzzy goal programming is another common approach to solve multi-objective problems under uncertainty. Yang et al. (1991) formulated the goal programming model as follows. Let $G_k(x)$ denote the kth fuzzy goal with a membership function $\mu_k[0,1]$. The membership function takes the value between 0 to 1 for the range of maximum and minimum allowable deviations from the goal. Then the resulting formulation is:

$$Max \quad \lambda_k \qquad \text{.........} \quad (46)$$

subject to

$$\lambda_k \leq \mu_k \qquad \text{.........} \quad (47)$$

$$\lambda_k, x \geq 0 \qquad \text{.........} \quad (48)$$

where λ_k is the level of satisfaction to attain the goal; μ_k is the membership function; and x is n-dimensional decision vector.

3.3 Deterministic Multiple Objective Problem - Multiple Decision Maker

The solution techniques for deterministic multi-objective multi-decision makers problem generally contain two steps – (a) solution for multiple objectives; and (b) solution for multiple participants. Methods for the former part have been described in the previous section of this report. In this section the general methods for multi-participant decision-making as summarized by Srisoepardani (2001) are presented. The methods are divided into three groups – (i) methods that perform the structuring of the problem; (ii) methods that perform measuring (ordering and ranking) of the problem; and (iii) methods that perform both structuring and measuring.

3.3.1 Methods for Structuring Multiple- Participant Problems

These methods provide fresh perspectives on a problem to create an alternative space from which meaningful and controllable distinct alternatives are likely to be identified. Analogy and attribute association; Boundary examination; Brainstorming; Brainwriting; Morphological connection; etc. are some of the methods in this class.

Brainstorming developed by Osborn (1953) is the most widely known and used group techniques. It is based on two principles and four fundamental rules. The two principles are 1) deferred judgment; and 2) quantity breeds quality. The four basic rules to guide a brainstorming session are 1) criticism is ruled out; 2) free-wheeling is overcomed; 3) quantity is wanted; and 4) combination and improvement are sought. The method is based on the premise that deferred judgments enhance creativity and that oral communication diminishes it. The main advantage of this method is that it produces a large number of ideas within a shorter period of time. The disadvantages include possibility of monopolization of a session by a group member; it's requirement of having members of equal status with basic familiarity with the problem; and it's applicability to relatively simple problems.

Brainwriting is a similar method with Brainstorming, except for using written ideas instead of verbal communication. The advantages are that dominance of stronger personality is eliminated and all members of the group can work in parallel. The disadvantages are that: (a) there will be inevitably duplication of ideas; and (b) it is not useful for large group size.

3.3.2 Methods for Ordering and Ranking Alternatives in a Multi-stakeholder Environment

The Nominal Group Technique (NGT) (Delbecq et el., 1975) takes advantage of the positive aspects of brainstorming and brainwriting and structured communication that improves alignment of group members' perception of the problem without working towards consensus. The steps of this method include: 1) introducing the meeting; 2) silently generating ideas in writing; 3) round-robin recording of ideas; 4) serial discussion for clarification; 5) preliminary vote on relative importance; 6) discussion of the preliminary vote; and 7) final vote. NGT has the advantages of brainwriting method, also it provides a sense of closure often not found in less-structured group methods. Disadvantages include it's capability to deal with only one question at a time; that it requires highly skilled leader and that the method becomes burdensome with a large size group.

The Delphi method (Turoff, 1970) is similar to NGT except that the group members do not meet face to face. Instead, a panel is used with members in communication remotely through several rounds of questionnaires transmitted in writing. Delphi is an expert opinio survey with three special features – anonymous response, iteration and controlled feedback, and statistical group response. Another advantage of this method is that it is possible to cover a wide geographic area and a large heterogeneous group that can participate on an equal basis. This method needs great deal of preparation due to the nature of written communication and is time consuming.

Voting elicits ordinal judgments and mathematically aggregates them into a group judgment. Two types of voting are nonranked voting system and preferential voting system. Nonranked voting is for two-alternative situation. Preferential voting is the method which allows the voter not only to indicate the most desired alternative, but also in what order or preference he/she would place the alternative. However, the problem of aggregating individual preferences to form a group choice remains as a subject of much discussion and controversy.

Disjointed incrementalism is a method to select the best policy based on its incremental consequences. This method was proposed to deal with complex policy decisions, typically in the government, in which a holistic approach for policy decisions is either impossible or impractical.

Conjoint measurement is concerned with predicting the values of a dependent variable by combining a set of independent variables in some functional form. The coefficients of the function are usually estimated by regression techniques.

3.3.3 Methods for Structuring and Measuring alternatives in a multi-stakeholder environment

Multiattribute Value Theory (MAVT) (Luce and Raiffa, 1957) attempts to maximize a decision maker's value (preference) which is represented by a function that maps an object measured on an absolute scale into the decision maker's utility or value relations. The function is constructed by, for example in the case of MAVT, asking lottery questions involving probability to articulate decision makers' value trade-offs among the conflicting attributes (objectives). Preferences are used in MAVT. The functional representation of a multi-objective problem is obtained by aggregating the different single attribute functions, each representing a different objective, by taking into consideration the relative weights of the objectives. Recent versions of *MAVT* have tended to look at the broad complexity of a problem within a structured framework and not simply as criteria and alternatives.

G*eneric utility theory* is designed as a general framework for multi-attribute utility modeling. A group utility or value function that takes the diversified evaluations of its individual members into consideration, can be obtained either by aggregating individual functions or by partial identification of the group function (Seo and Sakawa, 1985).

Game theory, which is based on the utility theory, is a mathematical technique for the analysis of conflict resolution. A conflict is comprised of participants who select various outcomes from a list of alternatives and the conflicting outcome may put the participants in competition. Game theory attempts to abstract the elements of such competitive situations, and put them into mathematical models to analyze them in a scientific way.

3.4 Multiple Objective Multiple Stakeholder Problem Under Uncertainty

Research is in progress to develop the methods to deal with multi-objective multiple-decision maker problems under uncertainty. These have been developed basically by combining the methods mentioned in the previous sections. A few works are described in this section to get the insight in the process that has been followed to arrive at a decision in multi-objective multi-stakeholder environment where uncertainties are considered.

3.4.1 Probabilistic Approach

Borsuk et al., (2001) described a decision-analytic approach to modeling a river management problem, focusing on linking scientific assessments of stakeholder objectives. The first step in the approach is elicitation and analysis of stakeholder concerns. The second step is construction of a probabilistic model that relates proposed management actions to attributes of interest to stakeholders.

Because of the complexity of the natural system and the need for a model to support decisions in the near term despite scientific uncertainty, a probabilistic model known as probability network has been adapted in this study. Probability networks are graphical models that depict probabilistic relationships among uncertain variables. These relationships among the system's variables can be used to perform both prediction and inference. With the model fully specified and validated, probability distributions (or risk profiles) can be produced for model endpoints, given particular sets of conditioning values. A decision maker then can visually compare the probabilistic profiles to assess the nature of risks associated with different alternatives.

The consideration of multiple participant plans can be facilitated by considering summary statistics, such as mean, medians, or exceedance probabilities. Alternatively, the risk profiles can be analyzed for stochastic dominance, allowing for rejection of clearly inferior alternatives. Finally, because the risks relate directly to endpoint variables that are meaningful to stakeholders, they can be evaluated in terms of associated costs and benefits, or by means of a multiattribute utility function to yield expected objectives.

3.4.2 Bayesian Analysis

Bayesian analysis is a popular statistical decision making process which provides a paradigm for updating information in the form of probabilities. It is based on the premise that decisions involving uncertainty can only be made with the aid of information about the uncertain environment in which the decision is made. Bayesian theory updates information by using Bayes theorem, a statement of conditional probabilities relating causes (states of nature) to outcomes.

Outcomes are results of experiments used to uncover the causes. Bayesian theory revises initial or prior probabilities of causes, known from a large sample of a population, into posterior probabilities by using the outcome of an experiment or test with a certain probability of success. Prior probabilities are obtained either subjectively or empirically by sampling the frequency of occurrence of a cause in a population. Posterior probabilities are those based on the prior probabilities and on both the outcome of the experiment and on the observed reliability of that experiment.

D'Ambrosio (web reference) demonstrated Bayesian method for collaborative decision making which prescribes that the optimal action to choose is the alternative that maximizes the subjective expected utility (SEU). The model consists of three elements – 1) a set of belief about the world; 2) a set of decision alternatives; and 3) a preference over the possible outcome of the action. The model avoids combining team members' evaluations by sampling from the entire space of preference, a function bounded by the individual member preferences. If the same choice is best everywhere in the space, then the choice is clear. If there are some parts of the space in which a different choice is preferred, then the analysis measures the spatial volume in which each choice is preferred. This volume can be interpreted as a probability that the choice is the best under a consensus preference model.

3.4.3 Fuzzy Approach

Blin (1974) showed that the notion of fuzzy preference over the set of alternatives can be applied to the group decision problem- where the decision maker becomes a collective entity and conflicts exist between individual preferences. It is noted first that the preference varies over the pair of alternatives in $A\times A$. There are certain pairs $(a_i, a_j)\in A\times A$ for which an individual or a group has a definite preference for the alternative a_i over a_j. Preferences on all other pairs cannot be represented by a simple 'yes' or 'no' statement, and therefore are stated as fuzzy preferences. Let us consider the closed unit interval [0,1] where strict definite preference over certain pairs can be assigned the value 1, and reciprocally if a_i is definitely preferred over a_j then the preference for a_j over a_i is assigned the value 0. All other pairs can be assigned preference values between 0 and 1. Formally we have a finite sequence of nested subsets, $S_{\alpha i}\subset S_{\alpha 2}\subset ......\subset S_{\alpha r}\subset A\times A$. Each subset $S_{\alpha i}$ is defined by a value $\alpha_i \in [0,1]$. All pairs $(a_k, a_t)\in A\times A$ whose preference level is at least α_i are in $S_{\alpha i}$. In other words

$$S_{\alpha i} = (a_k, a_t)\in A\times A \big| \mu_R(a_k, a_t)\geq \alpha_i \qquad \text{……….. (49)}$$

where $\mu_R(a_k, a_t)$ denotes the level of preference over the pair. In the fuzzy set terminology these $S_{\alpha i}$ are the α-level sets of a fuzzy relation R on $A\times A$ with membership function μ_R, and those sets form a nested sequence of nonfuzzy relation with $\alpha_i \geq \alpha_j \Rightarrow S_{\alpha i}\subset S_{\alpha j}$. According to Zadeh (1971) any fuzzy relation R on a set can be decomposed into the union of a class of non-fuzzy sets (the α-level sets) $S_{\alpha i}$:

$$R = \bigcup_{\alpha} S_{\alpha i} \qquad 0\leq \alpha_i \leq 1 \qquad \text{……….. (50)}$$

where each $S_{\alpha i}$ set is defined by the characteristic function

$$\mu S_{\alpha i}\left(a_k, a_t\right) = \begin{cases} \alpha_i & for\left(a_k, a_t\right) \in S_{\alpha i} \\ 0 & otherwise \end{cases} \quad \text{………..} \ (51)$$

The process of resolution of a fuzzy relation into a sequence of progressively weaker non-fuzzy relations provides a formal model of the notion of different degrees of preference. In the case of group decision making, the derivation of the non-fuzzy collective preference ordering from a fuzzy set of individual preference orderings of multiple decision makers depends on the selection rules for the collective choice. Using simple majority rule:

$$\mu_R\left(a_i, a_j\right) = \frac{1}{n} N\left|O_{ij}\right| \quad \text{………..} \ (52)$$

where n is the number of assessors, and $N\left|O_{ij}\right|$ denotes a total score (e.g. number of votes) for the pairwise preference ordering O_{ij} between the alternatives a_i and a_j .

The final ordering for the alternative can be obtained by mapping the fuzzy preference relations into a non-fuzzy ordering.

Kacprzyk and Nurmi (1998) presented the use of fuzzy preference relations and fuzzy majorities in the derivation of group decision making (social choice) solution concepts and degrees of consensus. Emphasis has been given on the use of the mentioned methods to derive more realistic and human consistent solutions when both preferences and majorities are imprecisely specified or perceived, and may be modeled by fuzzy relations and fuzzy sets.

If A (i, j = 1, 2, …….,n) alternatives are to be evaluated by K (k = 1, 2, …….m) individuals, first step is to construct a fuzzy preference relation matrix r_{ij}^{k} by pairwise comparison of the alternatives by each individual. Then the aggregation is performed to reach the consensus in the following way

To find out if A_i defeats A_j (h_{ij}^{k} = 1) or not (h_{ij}^{k} = 0), h_{ij}^{k} is calculated as:

$$h_{ij}^{k} = \begin{cases} 1 & if\, r_{ij}^{k} \prec 0.5 \\ 0 & otherwise \end{cases} \qquad \text{………} \quad (53)$$

Then h_j^k is calculated to find the level (0 to 1) at which individual k is not against A_j.

$$h_j^k = \frac{1}{n-1} \sum_{i=1, i \neq j}^{n} h_{ij}^{k} \qquad \text{………} \quad (54)$$

To get this for all the individuals, h_j is calculated as:

$$h_j = \frac{1}{m} \sum_{k=1}^{m} h_j^k \qquad \text{………} \quad (55)$$

Then, v_Q^j is computed which represent to what extent (0 to 1) most (Q) individuals are not against alternative A_j, which is

$$v_Q^j = \mu_Q(h_j) \qquad \text{.........} \quad (56)$$

Finally, the fuzzy set of alternatives that are not defeated by most (Q) of the individuals is expressed as the fuzzy Q-core:

$$C_Q = \{(A_1, v_Q^1), (A_2, v_Q^2), \text{.........}, (A_n, v_Q^n)\} \qquad \text{.........} \quad (57)$$

Here, fuzzy linguistic quantifiers as representations of a fuzzy majority have been employed to define a degree of consensus. This degree is meant to overcome some rigidness of the conventional concept of consensus in which consensus occurs only when all the decision makers agree to all alternatives.

Kwok et al. (2001) proposed a fuzzy Group Support System (GSS) to improve the quality of the group decision outcome. The method integrates (1) a fuzzy MCDM model; (2) a group supposrt system (GSS) and (3) structured group decision-making process. The fuzzy MCDM model includes fuzzy individual preference generation and group aggregation. Supported by the GSS, the structured decision making process makes group participation effective.

Fuzzy MCDM model

The proposed fuzzy MCDM model for group decision making integrates non-ranked voting method, particularly the approval voting method with fuzzy set theory. The model includes fuzzy individual preference generation and group aggregation.

Let $A = \{A_1, A_2 \ldots, A_m\}$, m>=3 be a finite set of alternatives; $C = \{C_1, C_2 \ldots, C_{t\}}$ be a given finite set of attributes or objectives; $P = \{P_1, P_2 \ldots, P_n\}$, n>=2, be a given finite set of decision makers. The steps of generating individual preferences are:

1. Considering the different importance of attribute C, the different weights to the attributes are determined using the Analytic Hierarchy Process (AHP). By pairwise comparison of the relative importance of attributes, the pairwise comparison matrix $E = [e_{ij}]_{t \times t}$ is established, where e_{ij} represents the quantified judgments on pairs of attributes C_i and C_j. The consistent weights for every attribute can be determined by calculating the normalized principal eigenvector. The weights are denoted as $w_1, w_2, \ldots., w_v$, where $w_i \in [0,1]$ and $\sum_{i=1}^{t} w_i = 1$.
2. Against every attribute C_j (j = 1, 2, ….., t), now should be assigned either 1 or 0 to preferred and unwanted alternatives respectively. The usual method of yes/no to choose or reject an alternative is sometimes difficult to be followed by the decision makers. Linguistic terms are used to assign belief levels containing various degrees of preferences required by the decision makers. The linguistic terms used are Z(belief) = {very sure, sure, not very sure, not sure} and are represented by specific membership functions for each term. The individual selections are denoted as two matrices: alternative selection matrix (v_{ij}) and belief matrix (b_{ij}) respectively, are $v_{ij} \in \{0,1\}$, $b_{ij} \in Z \cup \{0\}$ (i = 1, 2, ……, t; j = 1, 2, ….., m).

3. Then alternative selection matrix (v_{ij}) is aggregated to alternative selection vector (v'_j):

$$v'_j = w_1 \times v_{1j} + w_2 \times v_{2j} + \text{........} + w_t \times v_{tj} \qquad \text{… (58)}$$

and the belief matrix (b_{ij}) is aggregated to belief vector (b'_j):

$$b'_j = w_1 \bullet b_{1j} \oplus w_2 \bullet b_{2j} \oplus \text{........} \oplus w_t \bullet b_{tj} \qquad \text{.........} \quad (59)$$

4. The decision maker again makes overall judgment on alternatives based on the alternative selection vector and belief vector. The result is called individual selection vector.

5. All individual selection vectors are then composed by group selection matrix (b^g_{ij}). This is then aggregated into a group preference vector (r_j), j = 1, 2, ….., m, where each decision maker has an equal weight of 1/n. After ranking the group preference vector (r_j), the group can reach an agreement on the preferred alternatives.

Group Support System (GSS)

A Group support system is an interactive computer-based system that combines computing, communication and decision technologies to facilitate problem formulation and solution in collaborative work. Its goal is to ease the cognitive load of groups on particular decision-making tasks so as to improve the productivity, efficiency, and effectiveness of group meeting. In this study, the GSS has been used for brainstorming and evaluating alternatives for decision-making.

Structured Group Decision Making Process

A structured group decision-making process is proposed to facilitate the use of GSS and the fuzzy MCDM model. The steps are:

1. Brainstorm the basic alternatives
2. Evaluate the basic alternatives with reference to the decision criteria
3. Generate individual fuzzy preference on the basic alternatives
4. Aggregate individual preference to obtain decision outcome

If all the decision makers agree with the evaluation results, then the whole decision process ends, otherwise, decision makers may repeat the above steps in order to reach an appropriate level of group consensus.

4. DISCUSSIONS

In light of the experience gathered from this summary of multi-objective decision-making techniques, comments can be made on the applicability of these methods for the flood management decision-making in the Red River basin. As mentioned earlier, flood management problem in the Red River basin is a discrete type of problem, where a finite number of alternatives have to be evaluated before taking the decision. The evaluations are to be performed by a large number of decision makers (stakeholders) based on different non-commensurable objectives characterized by imprecision, indetermination and uncertainty. The approach taken by Blin (1974) and Kacprzyk and Nurmi (1998) used simple majority rule that is more applicable for larger number of participant. But in both cases, multiple objectives were not been considered, which leaves the scope to include multiple objectives with these approaches. The approach of Kwok et al. (2001) is a widely applied one, where the preferences of individual decision makers are aggregated to get the group decision. This approach suffers from lack of efficiency in case of a large number of decision makers. The use of linguistic variables to represent ordinal preference has been applied in all these works. But, in real world decision making situations, both linguistic expressions and numbers, are needed to express the decision makers' preference.

Applicability of fuzzy approach to represent imprecision and vagueness is highly recommended, as this approach can handle imprecision that is not possible to represent by probability analysis. Fuzzy multi-objective methods, like fuzzy compromise programming and fuzzy goal programming have been widely used in water resources planning problems, because these methods easily adapt to fuzzy inputs. Fuzzy goals, fuzzy weights and other fuzzy parameters bring these model closer to reality and the decision maker can extract the information necessary with greater accuracy, minimum loss of information and above all with higher satisfaction.

The possibility of collective fuzzy input into the two above mentioned methods can be explored as a new research idea to incorporate a large number of stakeholders in the decision making process. In compromise programming, if the fuzzy collective weight function can be constructed that would reflect the opinion of multiple stakeholders. In goal programming, the preference of the stakeholders in achieving different goals, as well as the degree of achievements can be represented by fuzzy membership functions. In both cases, the methodology to come up with these functions needs to be developed so that these reflect the collective opinions and conflicting judgments present in flood management problems.

5. CONCLUSIONS

A review of water resources multi-objective decision-making approaches has been made focusing on the issues of single and multiple decision makers under deterministic and uncertain conditions. Basic formulation of a multiple participant multi-objective decision making problem has been outlined for flood management in the Red River basin. Multiple objective decision making methods have been classified under four groups- (a) multiple participant single decision maker (deterministic); (b) multiple participant single decision maker (uncertain); (c) multiple participant multiple decision maker (deterministic); and (d) multiple participant multiple decision maker (uncertain).

Although the review is far from being complete, it can be concluded that there are a number of approaches to deal with multi-objective decision problem. The inclusion of multiple stakeholders is a growing line of research, where substantial works need to be done in order to handle a large number of decision makers. Fuzzy approach can be useful to handle multiple stakeholders, as well as to deal with uncertainties associated with the multi-objective decision-making.

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