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DEVELOPING A GROUP DECISION SUPPORT SYSTEM (GDSS) FOR DECISION MAKING UNDER UNCERTAINTY

by

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ABSTRACT

Multi-Criteria Decision Making (MCDM) problems are often associated with tradeoffs between performances of the available alternative solutions under decision making criteria. These problems become more complex when performances are associated with uncertainty. This study proposes a stochastic MCDM procedure that can handle uncertainty in MCDM problems. The proposed method converts a stochastic MCDM problem into many deterministic ones through a Monte-Carlo (MC) selection. Each deterministic problem is then solved using a range of MCDM methods and the ranking order of the alternatives is established for each deterministic MCDM. The final ranking of the alternatives can be determined based on winning probabilities and ranking distribution of the alternatives. Ranking probability distributions can help the decision-maker understand the risk associated with the overall ranking of the options. Therefore, the final selection of the best alternative can be affected by the risk tolerance of the decision-makers. A Group Decision Support System (GDSS) is developed here with a user-friendly interface to facilitate the application of the proposed MC-MCDM approach in real-world multi-participant decision making for an average user. The GDSS uses a range of decision making methods to increase the robustness of the decision analysis outputs and to help understand the sensitivity of the results to level of cooperation among the decision-makers. The decision analysis methods included in the GDSS are: 1) conventional MCDM methods (Maximin, Lexicographic, TOPSIS, SAW and Dominance), appropriate when there is a high cooperation level among the decision-makers; 2) social choice rules or voting methods (Condorcet Choice, Borda scoring, Plurality, Anti-Plurality, Median Voting, Hare System of voting, Majoritarian
Compromise, and Condorcet Practical), appropriate for cases with medium cooperation level among the decision-makers; and 3) Fallback Bargaining methods (Unanimity, Q-Approval and Fallback Bargaining with Impasse), appropriate for cases with non-cooperative decision-makers. To underline the utility of the proposed method and the developed GDSS in providing valuable insights into real-world hydro-environmental group decision making, the GDSS is applied to a benchmark example, namely the California’s Sacramento-San Joaquin Delta decision making problem. The implications of GDSS’ outputs (winning probabilities and ranking distributions) are discussed. Findings are compared with those of previous studies, which used other methods to solve this problem, to highlight the sensitivity of the results to the choice of decision analysis methods and/or different cooperation levels among the decision-makers.
To my Family

Without their support, this work would have not been possible.
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CHAPTER 1: INTRODUCTION

Research Problem Statement

Considering the increasing need for water in different industrial, agricultural and municipal sectors on one hand and scarcity and deteriorating quality of available freshwater resources on the other hand, optimal management and planning of water resources have become an issue of concern at regional, national, and international levels. Water plays a key role in sustainable development and water problems can affect economic growth, social welfare, or environmental well-being. Therefore, smart management solutions to current water resources problems cannot be developed by focusing on water quality or quantity issues. Developing comprehensive solutions to water management problems would not be possible without considering a range of objectives for water systems. Often, these objectives might be competitive in their nature. Therefore, they cannot be fully satisfied simultaneously. Thus, the main goal of the manager or the decision maker is to select the alternative that satisfies all considered objectives to the highest possible extent with a good understanding the involved trade-offs and associated risks with each solution.

To make a comprehensive decision with respect to different dimensions of water resources problems, reliable physical, hydrological, economic and socio-political data that can describe the characteristics of the system are required. However, the inherent uncertain nature of water resources-related data makes the decision making procedure even more complex. Multi-Criteria Decision Making (MCDM) methods provide a suitable framework for analyzing
decisions in water resources planning and management. Each MCDM method provides a unique definition of optimality based on which the performance of available alternatives and the relative importance of considered attributes should be considered to identify the best option. Due to clarity, efficiency, and explicit expression of the procedures, these methods have been used in several water and environmental resources studies (Romero and Rehman, 1987; Tkach and Simonovic, 1997; Lahdelma et al., 2000; Mendoza and Martins, 2006; Hajkowicz and Collins, 2007; Kiker et al. 2009). However, most MCDM methods can only handle deterministic problems in which all the required data (e.g. relative importance of considered attributes for different stakeholders and performance of alternative solutions under each attribute) should be known precisely. As a result, most water and environmental resources MCDM studies have only focused on deterministic problems. Little research has been carried out on incorporation of uncertainty into MCDM analysis (Hyde, 2006). The general procedure, followed in some studies (e.g. Triantaphyllou and Sanchez, 1997; Barron and Schmidt, 1988; Janssen, 1996; Butler et al., 1997) is to assume a value within the uncertainty range for the stochastic parameters (e.g., average of performance values) and by this means convert the stochastic problem into a deterministic one that can be handled using MCDM techniques. The effect of uncertainty then is evaluated using different sensitivity analysis methods. However, assuming a value for each uncertain parameter yields a deterministic answer for the stochastic problem which is hardly acceptable since no definite answer can be imagined for a problem with uncertain input parameters. Moreover, the proposed procedures are mostly applicable to a certain type of problems or methods (e.g. sensitivity analysis methods, proposed by Triantaphyllou and
Sanchez, 1997) or the theoretical approach has only been demonstrated and the application was not discussed (e.g. sensitivity analysis, discussed by Butler et al., 1997).

To prevent misinforming decision-makers about the risks associated with solutions to stochastic MCDM problems a different procedure is proposed in this study. The suggested method discretizes the uncertainty range into infinitesimal elements through Monte-Carlo selection, converting the stochastic problems into numerous deterministic ones that can be handled using different MCDM methods. The lumped results of all deterministic analyses then can be used to identify the probability for each alternative to be the optimal solution of the problem and the risk associated with the final order of alternatives.

Aims and Objectives

Considering the reviewed gaps in analysis of stochastic MCDM problems, the following objectives have been followed to introduce, apply and evaluate a new method for identifying the most probable optimal solution of stochastic MCDM problems and the risk, associated with the final decision.

- Objective 1: Since most classical MCDM methods are only applicable to deterministic input data, this study proposes the application of Monte-Carlo procedure for converting the stochastic problem into numerous deterministic ones. Each deterministic problem then can be analyzed using any MCDM method. The winning probability (the probability of being the optimal solution of the problem) of each alternative can be calculated using the lumped results of all deterministic problems and alternatives can be ranked based on their winning probabilities.
Therefore, the first objective of this study is to review the MC-MCDM method by explaining its mathematical background and the concept of winning probabilities for identifying the most probable optimal solution of the problem.

- **Objective 2:** The decision maker can single out the most probable solution using winning probabilities. However, this concept does not provide further information about other cases in which the winning option is suboptimal. Therefore, the decision maker remains unaware of the reliability of the winning option. Hence, knowledge of the winning probabilities would not be sufficient to make a decision with a high reliability. The second objective of this study is to consider ranking distribution (probability of taking different possible ranks) of each alternative as its robustness indicator.

- **Objective 3:** The MC-MCDM method is an iterative procedure, most suitable to be implemented by a computer. The Monte-Carlo selection should be repeated several times to ensure that all the points within the uncertain regions are participated in the analysis. Therefore, the third objective of this study is to develop a software package that can be used as a decision tool for deterministic or stochastic problems. This software package (Group Decision Support System or GDSS) integrates the Monte-Carlo selection procedure with some of the most well-known MCDM methods (i.e. Maximin, Dominance, Simple Additive Weighting, Lexicographic and Technique for Order Preference by Similarity to an Ideal Solution). Being normative (prescriptive), MCDM methods are suitable for decision making problems with a high level of cooperation among the decision-
makers or MCDM problems with a single decision maker. To enable the GDSS for decision analysis in less cooperative conditions, two other categories of decision making methods, namely Social Choice Rules (for medium cooperation level) and Fallback Bargaining methods (for low cooperation level) will be also included in this software package.

- Objective 4: The final objective of this study is to evaluate the efficiency and applicability of MC-MCDM method to real-world problems. Therefore, GDSS will be used to apply the suggested MC-MCDM method to California’s Sacramento-San Joaquin Delta decision making problem as a benchmark example. Winning probabilities and ranking distributions of alternative solutions for exporting water from California’s Sacramento-San Joaquin Delta are calculated using the GDSS software and results will be compared with those of former studies which applied other methods to solve this benchmark problem.

**Organization of Thesis**

The second chapter of this study provides detailed review of five MCDM methods (i.e. Dominance, Maximin, Lexicographic, TOPSIS and SAW) that are used in this study to explain the MC-MCDM method. A brief introduction to some other well-known MCDM methods along with a brief review of major studies on incorporating uncertainty in MCDM analysis is provided later in this chapter. The third chapter is dedicated to review of the proposed MC-MCDM method. Application of this method to stochastic input data along with calculation and interpretation of winning probabilities and ranking distributions are discussed in this chapter.
Details of the Group Decision Support System (GDSS) are introduced in chapter four. Different subroutines of GDSS are introduced and their corresponding user interfaces are presented in this chapter. In chapter five, the proposed MC-MCDM method is applied using GDSS, to calculate the winning probabilities and ranking distributions of four alternative solutions of California’s Sacramento–San Joaquin Delta water export problem. The results are interpreted and compared to those of former studies. Chapter 6 summarizes this study and presents its major conclusions.
CHAPTER 2: MULTI-CRITERIA DECISION MAKING (MCDM) METHODS

Multi-Criteria Decision Making (MCDM)

As a branch of Operations Research (OR) Multi-Criteria Decision Making (MCDM) is ONE of the most well-known decision analysis methods (Triantaphyllou and Sanchez, 1997). MCDM methods allow a decision-maker to single out the best option or rank a finite set of alternatives considering different criteria. According to Sun and Li (2008) more than seventy MCDM methods have been developed over the four decade history of this discipline.

Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM) can be considered as two branches of MCDM. MODM methods handle decision making problems in continuous decision domain while MADM methods are suitable for problems with discrete (normally pre-defined) alternatives. Although MADM methods are different in their definition of optimality, assumptions, and mathematical procedure, they follow a unique overall scheme. The general procedure of a MADM is shown in Figure 1 (Pohekar and Ramachandran, 2004).
Since MADM methods are following the same overall procedure, they have some terms and notions in common. Short descriptions of such terms are provided next.

- *Alternatives*: are the options available, among which the decision-maker has to find the best one, through MADM. As mentioned earlier, in MADM, the number of alternatives is limited.
- **Criteria**: are different attributes or qualities based on which the alternatives can be evaluated. In MADM they are also recognized as goals or objectives.

- **Alternative’s performance measure**: is the performance or payoff of an alternative under a criterion or the degree that an alternative fulfils a goal.

- **Criteria weight**: is the relative importance of each criterion compared to all others.

- **Decision matrix**: is an m×n matrix, where m is the number of alternatives and n is the number of criteria. Each element of the decision matrix, a_{ij}, represents the performance measure of alternative i (i from 1 to m) under criterion j (j from 1 to n).

There are many ways to classify MADM methods. Based on the type of alternatives’ performance measures, MADM procedures have been classified into deterministic and stochastic methods. In a deterministic MADM problem, performance measures are fixed deterministic values while in a stochastic MADM problem, performance measures can be given as intervals of possible values with different probability distributions. Based on the number of decision makers involved, MADM methods can be categorized into single decision-maker MADMs and multi-participant MADMs (Madani and Lund, 2011). Based on their mathematical formulation, MADM methods can be compensatory or non-compensatory. In a compensatory method performances of an alternative under different criteria are aggregated; hence, a weak performance under one criterion can be compensated by a high payoff under another. However, in non-compensatory methods performance of alternatives under each criterion are assessed independently. Readers interested in other classifications of MADM methods may consult Hwang and Yoon (1981). It should be noted that in the decision analysis literature, Multi-Criteria
Decision Making (MCDM), Multi-Attribute Decision Analysis (MADM) and Multi-Criteria Decision Analysis (MCDA) have been used interchangeably (Hyde, 2006).

Commonly Used MCDM Methods

*Dominance (Fishburne 1964)*

Dominance is one of the oldest yet most fundamental concepts of decision making. Application of the dominance method requires a pairwise comparison of all alternatives to identify the non-dominated option (Figueria et al., 2005). In comparison of two options, the dominant alternative excels under one or more criteria and equals under the remaining ones (Hwang, 1981).

Application of dominance method takes the following steps (Calpine et al., 1976):

- Comparing the first two alternatives (a pairwise comparison);
- Identifying the dominant alternative;
- Discarding the dominated alternative and replacing it with another alternative;
- Repeating the procedure until the final winner is recognized;

After stepwise elimination of alternatives based on their performance score under all criteria, the dominance method identifies one or more options that are at least as preferable as all other alternatives (DCLG, 2009). It should be mentioned that during each pairwise comparison, performance measures of the alternatives under each criterion are assessed independent of their performances under other criteria. Therefore, dominance is a non-compensatory method. In simple words, good performance of an alternative under a set of criteria cannot compensate its
bad performance under other criteria (Sun and Li, 2008). Having this characteristic (no aggregation of performances under different criteria), the dominance method is applicable to problems with incommensurable attributes as well as problems with both qualitative and quantitative data. Therefore this method can be used in many practical problems in which limited data is available on the performance of alternatives (ODPM, 2004). For further description and an example application of dominance method see Jankowski (1995). Example applications of the Dominance method in the water and environmental resources context include Matthews (2001), Greeninga and Bernowb (2004), Mokhtari et al. (2012) and Read et al. (2013).

Dominance method cannot evaluate the degree of superiority of one alternative over the others since the method does not consider the difference of payoffs but only compares them. In other words, dominance method is based on ordinal information. The other drawback of this method is that it can rarely selects a unique alternative as the winner as in most cases there is no alternative that dominates or is dominated by all other options. To deal with this drawback, a similar but more flexible approach has been followed to find the best option. Based on the modified method, the winning alternative is not required to dominate all other alternatives. The alternative that has a better performance than others in most of the pairwise comparisons under all criteria is considered to be the optimal solution. Application of this method can be summarized into the following steps:

- Comparing the first two alternatives’ performances under different criteria;
- Determining the number of attributes under which each alternative dominates or is dominated by the other options;
- Repeating the procedure until all alternatives have been pairwise compared;
- Summing up all the wins and losses of each alternative; and
- Selecting the alternative that has the maximum number of wins and the minimum number of losses as the winning solution.

Following this procedure, rank of each option can be determined using the number of wins and losses.

**Maximin (Wald, 1945)**

As a conservative (risk-averse) decision making approach, the Maximin method tries to avoid the worst possible outcome (Linkov et al. 2005). Maximin ranks alternatives based on their weakest attribute (Norris and Marshall, 1995). In this way, the decision-maker is insured that the worst outcome is avoided.

The Maximin method selects the alternative with the maximum lowest performance as the optimal solution (Pazek and Rozman, 2008). Since, identification of the minimum payoff of each alternative requires comparison of its performances under all criteria, the performance values need to be commensurable. Practical problems rarely satisfy this requirement. Therefore, performance measures could be normalized in order to use the Maximin method (Greening and Bernow, 2004). Similar to the dominance method, Maximin does not require weighting. However, unlike the dominance method, Maximin can only handle cardinal performance data since minimum payoffs could not be identified using ordinal performance measures.

Maximizing the minimum satisfaction of all criteria involves the following steps:
- In case of incommensurable units, performances of alternatives under different criteria are normalized;
- Minimum performance of each alternative under all criteria should is identified;
- The alternative that has the highest minimum performance, is the winner of Wald’s Maximin criteria; and
- If needed, the overall ranking of other alternatives are determined through comparison of their minimum performance values.

*Lexicographic (Tversky, 1969)*

As can be inferred from its name, a decision-maker who uses a lexicographic strategy tries to satisfy the most important attribute (Greening and Bernow 2004, Jankowski 1995, Dillon 1998). In lexicographic alphabetizing of words in a dictionary, letters are the criteria and their preference order (‘A’ better than ‘B’ better than ‘C’ and so forth) determines the ranking of the words (Norris and Marshall, 1995). Similarly, in lexicographic decision making, all considered criteria are ordered based on their importance. Then, the alternative with the highest performance under the most important criterion is selected as the optimal alternative. In case of a tie, which is likely in problems with several alternatives, performances of tying options under the next most important criterion determine the best alternative. The procedure will continue, in case of another tie, until a unique winner alternative can be identified (Linkov et al., 2005).

Given the description of the method, the first step is to determine the importance or weight of each criterion. Therefore, unlike previously discussed methods, the lexicographic method requires prioritization of the criteria based on their weight or importance. The lexicographic method can be classified as a non-compensatory method, since no aggregation of performance values is required. This method can handle quantitative as well as qualitative
performance values and the analysis of incommensurable attributes does not require initial normalization.

In order to rank the alternatives using lexicographic method, an elimination procedure can be followed where the winner is eliminated from the list of available alternatives and the procedure is repeated for the remaining options. The stepwise application of the lexicographic method is as follows:

- Criteria (attributes) are ranked based on their importance or weight;
- The alternative with the highest performance under the most important criterion is the winner of lexicographic procedure;
- If two or more alternatives have equal performances under the most important criterion, comparison of their payoffs under the next most important criterion determines the winner;
- To find the ranking of all alternatives the winner can be eliminated from the list of alternatives and the procedure is repeated for the remaining options

**Simple Additive Weighting (Churchman and Ackoff 1945)**

Simple additive weighting (SAW) is one of the most popular MCDM methods that rank alternatives by additive aggregation of their performance values under all criteria (Yilmaz and Harmancioglu 2010, Norris and Marshall 1995, Pearman 1993). Example application of this method to water resources and environmental problems include Fassio et al. (2005), Giopponi (2007), and Madani et al. (2013). Due to its simplicity, it became the basis of other decision making methods (e.g. AHP and PROMETHEE) that use an additive aggregation approach to
evaluate the alternatives (Memariani et al. 2009). Based on the SAW method, weighted performances of alternatives under all criteria are the bases for comparison (Triantaphyllou 2000). Application of this method requires calculation or measurement of relative importance or weight of each criterion. Based on this method, a comparison index of an alternative (SAW$_i$) is calculated using Equation 1.

$$SAW_i = \sum_{j=1}^{n} W_j \times r_{ij}$$  \hspace{1cm} (1)

where: SAW$_i$ is the comparison index for alternative i, n is the number of criteria, $W_j$ is the weight of criteria j, and $r_{ij}$ is the performance of alternative i under criterion j.

The higher the comparison index of an alternative, the better the alternative. SAW is a compensatory method, i.e. the low payoff of an alternative under some criteria, can be compensated by better performance under other attributes. In order to use SAW, performance values should be numerical (quantitative) as well as comparable (commensurable). To deal with incommensurable units, performance values can be normalized. However, SAW is very sensitive to the normalization method. Changing (adding or removing) alternatives from the problem can also affect the SAW results drastically (Triantaphyllou 2000).

Application of the SAW method involves the following steps:

- Weight of each criterion are calculated or measured;
- In case of incommensurable criteria, performances are normalized;
- Performance vector of each alternative under all criteria are converted to a scalar index using Equation 1;
- Alternatives are ranked based on the comparison index values.
TOPSIS (Hwang and Yoon 1981)

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method selects the alternative that has the minimum relative distance from the ideal performance as the best alternative. The main idea behind TOPSIS method is that alternatives can be imagined as points in a geometric space where criteria are different dimensions. In simple words, a problem of n alternatives and m criteria can be presented as n points in an m-dimensional space (Hwang and Yoon 1981). In this space, imaginary ideal and nadir points (positive and negative ideals, respectively) can be defined such that their coordinates are the best and worst performances of alternatives under different criteria. Then using basic geometry, distance of each point (alternative) from ideal and nadir points can be determined. Ranking of alternatives can be identified then by calculating a similarity index or relative closeness that combines the closeness of each option to the positive-ideal and remoteness from the negative-ideal. This method was first developed by Hwang and Yoon (1981). In 1982, a similar concept was also suggested by Zeleny (1982).

TOPSIS is a simple method and has been used in several economic and management problems in the past decades (Shih et al. 2007). Example applications of this method in the water and environmental resources management literature include Li (2009), Mokhtari et al. (2011), Madani et al. (2013), Cheng et al (2006) and Srdjevic et al. (2004). The fact that it uses performance values directly rather than pair-wise comparison makes it more suitable for problems with numerous alternatives in which the comparison-based methods become impractical (Lafleur and Guggenheim 2011). However, like most of the classical MCDM methods, the performance values of alternatives and weights of criteria should be known (Lafleur
and Guggenheim 2011). Moreover, the method does not consider the relative importance of the distances from ideal and nadir points and they are both equally important in determining the best option (Wu et al. 2012). The TOPSIS method can be applied through the following steps:

- The performances are normalized using Equation 2.

\[ N_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}} \]  

where \( N_{ij} \) is the normalized performance of alternative \( i \) under criterion \( j \), \( m \) is the number of criteria, and \( r_{ij} \) is the performance of alternative \( i \) under criterion \( j \).

- The weighted normalized performance of each alternative under each criterion \( (V_{ij}) \) is calculated using Equation 3.

\[ V_{ij} = N_{ij} \cdot W_j \]  

where \( V_{ij} \) is the weighted performance of alternative \( i \) under criterion \( j \) and \( W_j \) is the weight of criteria \( j \).

- The best and worst performances of the alternatives under each criterion \( (V_j^+ \text{ and } V_j^-) \), respectively) are determined based on the weighted normalized decision matrix.

- Distances of each alternative from the best and the worst performances are calculated using Equations 7 and 8, respectively.

\[ d_i^+ = \left[ \sum_{j=1}^{n} (V_{ij} - V_j^+)^2 \right]^{0.5} \]  
\[ d_i^- = \left[ \sum_{j=1}^{n} (V_{ij} - V_j^-)^2 \right]^{0.5} \]
where $V_j^+$ is the best performance of alternatives, $V_j^-$ is the worst performance of alternatives and $d_i^+$ and $d_i^-$ are the distances from these two values, respectively.

- The relative distance ($CL_i^+$) of each alternative is calculated using Equation 6.

$$CL_i^+ = \frac{d_i^+}{d_i^+ + d_i^-}$$  \hspace{1cm} (6)

where $CL_i^+$ is the relative distance from the best and the worst performance of alternatives.

Options are ranked based on their relative distance where the alternative with the smallest relative distance is selected as the best alternative.

**Other MCDM Methods**

*Analytic Hierarchy Process (Satty, 1980)*

The AHP method is essentially the mathematical expression of human’s psychological perception of complex problems in a hierarchical manner (Saaty, 2008). For analysing a decision making problem using the AHP method, the problem should be formatted using a hierarchical structure where the main objective is at the top, considered criteria are in the middle, and alternatives are at the bottom (DCLG, 2009). The criteria in the second level can be prioritized then through a pair-wise comparison. In each comparison a value in scale of one to nine (one being extremely marginal and nine being extremely important) will be assigned to more important criterion. The reciprocal of the assigned value will be then assigned to the less important option. Weight of each criterion is then determined by normalizing and averaging all the importance values assigned to that criterion. The same procedure is followed for all
alternatives under each criterion so that the relative superiority of alternatives under each
criterion can be determined. Finally, the overall score of each alternative can be calculated using
a weighted summation of relative importance values. In simple words, similar to SAW, the
assigned values to each alternative under each criterion will be multiplied by the weight of this
criterion. Summation of weighted values yields an overall score for each option which can be
used for ranking of alternatives.

By decomposition of the problem into a hierarchical order, the AHP method can provide
better insights into the problem and help the decision maker with understanding trade-offs of the
considered attributes. This method has been widely used in water and environmental resources
studies (Hajeeh and Al-Othman, 2005; Willett and Sharda, 1991; Srdjevic, 2007; Jaber and
Mohsen, 2001; Srdjevic and Medeiros, 2008; Zhang, 2008; Ying et al., 2008). However, since
AHP is a compensatory method, in aggregating all the good and bad performances of each
alternative under all criteria, some important information regarding performance of alternative
might be lost in forming the final decision (DCLG, 2009). Moreover, ranking irregularities have
been observed in many AHP applications. For instance, when an irrelevant alternative (e.g. a
copy of one of the alternatives) was added to the decision making problem, changes in final
ranking have been observed (DCLG, 2004). Using a counter-example, Lund (1994) showed that
the results of AHP method can be different from those obtained by direct application of value
theory principles and concluded that AHP might violate its basic principles. During an analytic
hierarchy process several pair-wise comparisons are required. Therefore, application of this
method to problems with large number of alternatives and criteria is tedious. Another drawback
of AHP is its limited 1-9 scale. In practical cases, accurate evaluation of criteria and alternatives
in the restricted scale can be difficult. For instance, application of AHP can be confusing for the decision-maker when one criterion is more than nine times more important than another one.

Conjunctive and Disjunctive Methods

Conjunctive and disjunctive methods have been referred to as “satisfying” methods since they are not used to single out an alternative as the optimal solution of the problem, but to divide alternative into acceptable and unacceptable groups (Hwang & Yoon, 1981). Unlike other methods, conjunctive and disjunctive procedures have not been very popular in water and environmental resource management studies. In conjunctive methods, an alternative should maintain a higher payoff than minimum requirement under each criterion. Thus, an alternative will be considered unacceptable if it fails to meet the minimum requirement of at least one criterion. In a very similar procedure, under disjunctive method, alternatives should exceed a minimum requirement of one or more criteria. For both of these non-compensatory methods, decision-maker should define the minimum acceptable values for all criteria.

Weighted Product Method (Bridgman, 1922)

The weighted product method (WPM) is very similar to SAW. But, the two methods are different in two main respects. First, instead of addition, WPM uses multiplication for aggregation of performance values (Pohekar and Ramachandran 2004). Second, SAW requires normalization of payoffs for incommensurable criteria. However, WPM is a dimensionless analysis since all units will be eliminated through the procedure (Triantaphyllou, 2000).
In WPM, weights of criteria are set as the exponents of alternatives’ payoffs and a comparison index is calculated for each alternative by multiplying all the powered performance values. Equation 7 presents the mathematical basis of such calculation.

$$WPM_i = \prod_{j=1}^{n} r_{ij}^{w_j} \quad (7)$$

where $WPM_i$ is the comparison index for alternative $i$, $W_j$ is the weight of criteria $j$, and $r_{ij}$ is the performance of alternative $i$ under criterion $j$.

WPM has been proposed by Bridgman in 1922 and has not been used widely despite the fact that it requires the same type of information as most other MCDM methods.

**ELECTRE (Roy, 1971)**

The ELECTRE (ELimination Et Choix Traduisant La Réalité) method uses outranking relations for identifying the most preferred option. An outranking relation can express the likely preference of an alternative over another (Hwang and Yoon, 1981). Using performance values of alternatives, decision criteria can be divided into two distinct groups, namely concordance and discordance sets, in each pair-wise comparison. Concordance set consists of all criteria under which one alternative outranks another one and discordance set can define for the reverse relation. The mathematical expressions of concordance and discordance sets are given in Equations 8 and 9, respectively.

$$C(A, B) = \{j|v_{Aj} \geq v_{Bj}\} \quad j = 1, \ldots, m \quad (8)$$

$$D(A, B) = \{j|v_{Aj} \leq v_{Bj}\} \quad j = 1, \ldots, m \quad (9)$$
where \( m \) is the number of criteria, \( A \) and \( B \) are the selected alternatives for pair-wise comparison, and \( v_{Aj} \) and \( v_{Bj} \) are the performances of alternative \( A \) and \( B \) under criteria \( j \), respectively.

In the next step, power of each set will be determined by the concordance and discordance indices (Equations 10 and 11, respectively).

\[
C_{AB} = \sum_{j^*} w_{j^*} \tag{10}
\]

\[
D_{AB} = \frac{(\sum_{j^0} |v_{Aj^0} - v_{Bj^0}|)}{(\sum_j |v_{Aj} - v_{Bj}|)} \tag{11}
\]

where \( j^0 \) represent criteria in the discordance set \( D(A,B) \) and \( j^* \) represents criteria in the concordance set \( C(A,B) \).

Finally, dominance relations can be evaluated using the concordance and discordance indices, leading to the overall ranking of all alternatives.

Similar to most other MCDM methods, ELECTRE needs criteria weights as well as the quantitative performance values. Forming the outranking relations and calculating the concordance and discordance indices for problems with several alternatives and criteria can be challenging. Nevertheless, ELECTRE is one of the most popular MCDM methods (Hwang and Yoon 1981) and has been utilized in many water and environmental resources studies (Raju et al. 2000; Hobbs, 1992; Bender and Simonovic, 2000; Gershon et al., 1982; Raj, 1995; Bella, 1996; and Roy et al., 1992).
Uncertainty in Decision Making

Uncertainty is one of the main sources of complexity in decision analysis and it has been the subject of several studies in this field (Triantaphyllou and Sanchez, 1997; Barrob and Schmidt, 1988; Janssen, 1996; Hyde, 2006; Butler et al., 1997). Uncertainty can enter decision making from different sources in each step of analysis. Imprecision in measurements and estimations of alternatives’ performance and criteria’s relative importance are the major sources of uncertainty in input data. In modeling and post-analysis procedures, choosing the appropriate model (optimality concept) and interpretation of the results can lead to uncertainties.

Different sensitivity analysis (Triantaphyllou and Sanchez, 1997; Barron and Schmidt, 1988; Janssen, 1996; Hyde, 2006; Butler et al., 1997), fuzzy decision making (Wang, 2009; Bender and Siminovic, 2000; Blin, 1974; Siskos, 1982; Felix, 1994; Triantaphyllou and Lin, 1996) and other methods (Ben Abdelaziz et al., 1999; Lahdelma and Salminen, 2002; Nowak, 2007; Ben Abdelaziz et al., 2007) have been proposed to deal with uncertainty in criteria weights and alternatives’ performance values (Madani and Lund 2011).

An intuitive approach in stochastic MCDM studies is to assume or calculate the most probable value for each uncertain variable (alternatives’ performance measure or criterion’s weight) so that the stochastic problem can be handled like a deterministic one using MCDM methods. Then, the uncertainty effects can be evaluated using sensitivity analysis. Following this approach, different methods have been proposed, some of which are discussed in this chapter.

The general procedure in fuzzy MCDM methods is to rate the alternatives based on the degree of satisfaction they provide under each criterion and then rank them, based on aggregated
ratings under all criteria. A brief review of major works on application of MCDM methods to fuzzy data is provided in this chapter.

Fuzzy MCDM methods

Application of MCDM methods to fuzzy information was another subject of interest in decision making under uncertainty over the past four decades. In many real world problems, due to complexities of measurement, alternatives’ performances or criteria weights are described imprecisely, sometimes in vague linguistic terms. In 1965, Zadeh proposed employing the fuzzy set theory for modelling systems with non-deterministic input parameters. The term fuzzy, generally refers to problems without crisp input data (Kahraman, 2008). In fuzzy logic, as opposed to Boolean logic, statements are not either right or wrong. Instead, they can belong to both sets to some degree. Therefore, fuzzy logic provides a more flexible membership relation than Boolean logic since statements can be partial members of true and false sets.

As mentioned earlier, classic MCDM methods are only applicable when precise information regarding performance of alternatives and criteria weights are available (crisp values). Therefore, application of these methods to vaguely or linguistically expressed information requires a proper method for converting such data to conventional input. The general approach in most Fuzzy MCDM methods can be divided into two steps. During the first step, rating process, the degree of satisfaction for each alternative under each criterion is determined. Aggregation of these ratings for each alternative can be used in the second step to rank available options (Zimmermann, 1987; Chen and Hwang, 1992; Ribeiro, 1996).
Fuzzy MCDM (FMCDM) was first introduced by Bellman and Zadeh in 1970. In their study, they sketched a general framework for application of MCDM methods to fuzzy data by defining goals and constrains as fuzzy sets in the space of alternatives. Maximizing decision was then defined as the set of points that maximizes the membership function of the decision. Baas and Kwakernaak (1977) proposed a classic FMCDM method that has been regarded as the touchstone of many later works in this field (Kahraman, 2008). Considering the uncertain input data as fuzzy quantities that can be expressed by proper membership functions, they proposed a method for evaluation and ranking alternatives in multi-aspect decision making problems (Bass and Kwakernaak, 1997). In a more recent study, Ling (2006) used arithmetic operations and expected value of fuzzy variables (criteria weights and decision matrix elements) to solve FMCDM problems. Among different MCDM methods, Analytical Hierarchy Process (AHP) was the subject of many FMCDM studies (Buckley, 1985; Chang, 1996; Weck et al., 1997; Zhu et al., 1999). Earliest work on fuzzy AHP was carried out by van Laarhoven and Pedrycz (1983) which used triangular membership functions to calculate ratios for fuzzy parameters. Study of fuzzy outranking methods (e.g. ELECTRE), on the other hand, is very recent and the literature is not well documented (Kahraman, 2008). Review of fuzzy theory in MCDM analysis can be found at Kickert (1978), Chen and Hwang (1992) and Sakawa (1993).

Several studies applied fuzzy MCDM methods to water resources management problems. Merging stochastic fuzzy approach with Ordered Weighted Averaging (OWA), Zarghami and Szidarovszky (2009) evaluated the management problems of Tisza River in Hungary. Gu and Tank (1997) Used fuzzy MCDM to adjust the monthly reservoir operations and find the optimal operation tasks for Qinhuangdao water resources management. In another study, Opricovic
(2011) proposed a fuzzy VIKOR approach for evaluating the flow condition of Mlava River and its tributaries for regional water supply. In this study a triangular membership function was assumed for fuzzy parameters (alternatives performance and criteria weights). Other applications of fuzzy MCDM method can be found at Bogardy and Bardossy (1983); Bender and Simonovic (2000); Raju et al. (2000); Chang et al. (2008) and Chen et al. (2011).

*Sensitivity analysis methods*

The main purpose of sensitivity analysis is to evaluate the robustness of optimal solution (selected by MCDM methods) to the change in input data. In simple words, most sensitivity analysis methods try to measure the minimum required change in input values that can change the ranking of the best alternative. Barron and Schmidt (1988) proposed two sensitivity analysis methods for dealing with stochastic MCDM problems. The first one is an entropy-based method, which can be applied when criteria weights are equal. Using this method, the closest equal criteria weights to the initial values that can reverse the order of the best alternative with any other options can be calculated. The second method, least squares procedure, can be applied for any arbitrary values of weights. This method can calculate the closest weights to the initial values that can reverse the order. In another study, Janssen (1996) proposed a method for calculating the intervals within which the ranking of considered alternatives are not sensitive to variation of criteria weights or performance measures (Hyde 2006). Three different sensitivity analysis methods for three MCDM methods (WSM, WPM and AHP) were introduced by Triantaphyllou and Sanchez (1997) to evaluate the sensitivity of selected option to changes in decision criteria weights. Since the considered MCDM methods are using weighted performance
of alternatives, they proposed a procedure for converting the uncertainty in performance measures of alternatives into criteria weights so that both major sources of uncertainty (alternatives performances and criteria weights) can be evaluated using these methods.

The reviewed methods yield a deterministic answer for the stochastic problem, while a definite solution to problems with stochastic (uncertain) input parameters must not be logically acceptable. Moreover, in stochastic problems the values within the intervals that present the performance measures of alternatives or criteria weights can follow a probabilistic distribution. Janssen (1996) assumed a normal distribution of values for each input data and converted a stochastic problem into numerous deterministic ones using a Monte-Carlo procedure. The results of this method can determine the probability of each alternative for being the optimal solution of the problem. However, this work only considered a normal distribution of input data, which might not be the case in many problems. Moreover, in this study, one interval was analyzed in each round of Monte-Carlo selection. Therefore, the effect of simultaneous change in input variables was neglected. In another study, Butler et al. (1997) proposed a sensitivity analysis for MCDM methods that aggregate performance values under different criteria. Their suggested method considers the simultaneous effects of change in input values, but is only applicable to criteria weights. Furthermore, the implementation procedure of this method has not been discussed in their work.

This thesis argues the methods that provide a definite solution to stochastic decision making problems misinform the decision maker by ignoring the associated risk with the definite solution. To bridge the current gap, a Monte-Carlo MCDM method is suggested to facilitate informed group decision making in face of uncertainty. The suggested method maps the complex
uncertainty in input variables to uncertainty in outputs in simple terms, understandable to the
decision-makers. Mathematical details of the suggested method are presented in the next chapter.
CHAPTER 3: MONTE-CARLO MULTI-CRITERIA DECISION MAKING AND RELIABILITY ASSESSMENT

Introduction

In this chapter, application of MCDM methods to stochastic decision making problems through a Monte-Carlo selection is suggested. First, the mathematical basis and application procedure are explained. Then, results interpretation and analysis are discussed. In application of the suggested Monte-Carlo Multi-Criteria Decision Making (MC-MCDM) method two distinct approaches can be followed to evaluate alternatives. These approaches provide two different types of valuable information about the alternatives:

1) Winning probability: the probability of an alternative being the optimal (best) solution for the problem; and

2) Ranking distributions: probabilities of selected at different ranks.

Winning probabilities help identifying the likely optimal solution of the problem while ranking distributions can be used to evaluate the robustness or reliability of decisions in a stochastic domain. Using these two concepts, the later part of this chapter argues that the most probable optimal solution of a stochastic decision making problem with the highest winning probability might not be the most reliable solution necessarily.

The suggested Monte-Carlo Multi-Criteria Decision Making (MC-MCDM) method is a repetitive procedure to be implemented by a computer. Like most other repetitive analyses, post analysis control is required to ensure that the outcomes are reliable. For instance, one should
ensure that the results have converged and the calculated probability distributions are consistent.
The necessary post-analysis steps are discussed at the end of this chapter.

Monte-Carlo Multi-Criteria Decision Making (MC-MCDM)

In stochastic MCDM problems, feasible performance values of alternatives can be considered as discrete regions in the space, formed by decision attributes. In other words, if criteria are to be considered as a set of perpendicular axes, the performance measures of an alternative in the feasible performance space will form a performance space of this alternative. The projection of this performance space on each criterion axis is the performance range of the alternative under that criterion. To illustrate this concept, a simple example problem with two alternatives and two criteria is assumed (Table 1).

Table 1 Performance measures of the example stochastic MCDM problem

<table>
<thead>
<tr>
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<th>Criterion 1</th>
<th>Criterion 2</th>
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</thead>
<tbody>
<tr>
<td>Alternative 1</td>
<td>[5,10]</td>
<td>[25,75]</td>
</tr>
<tr>
<td>Alternative 2</td>
<td>[7.5,12.5]</td>
<td>[50,100]</td>
</tr>
</tbody>
</table>

The performance space of the alternatives in the example problem is two-dimensional since the alternatives should be evaluated under two criteria. Considering the payoff of each option under each attribute, feasible performance values form rectangular performance regions in this feasible solution space as presented in Figure 2. Coordinates of any point within each rectangle are deterministic values belonging to the performance ranges. It should be noted that the probability distribution of payoffs over such regions do not need to be uniform necessarily.
Classical MCDM methods provide different definitions of the best solution due to different notions of optimality. Based on their definition, they can identify the optimal solution among a finite set of alternatives by evaluating their performances under a finite set of criteria. However, for application of these methods the performance values should be deterministic values (single discrete numbers as opposed to intervals). To apply MCDM methods to stochastic decision making problems, alternatives’ performance space should be discretized into its numerous points. Each point, representing a deterministic value, can then be used in a deterministic MCDM analysis. Such discretization can be performed using a Monte-Carlo selection. Through a repetitive procedure, in each round of Monte-Carlo selection, a single random point with fixed coordinates will be selected from each alternative’s performance space with respect to probability distribution of performance values over the performance space. Alternatives with fixed coordinates are then compared and the MCDM methods can be applied to rank them and select the best alternative in each round of random selection. Theoretically, infinite repetition of the procedure ensures that all points within the feasible space participate in
the analysis. However, in practice, this is done through a large number of iterations and controlling the convergence of results. Results of each selection round are recorded and the overall goodness of an alternative is determined at the end of the procedure by considering the number of times it is ranked at different levels. In short, the suggested MC-MCDM method first converts a stochastic problem into numerous deterministic ones, and then solves each deterministic problem using a MCDM method. Finally the results of all iterations will be aggregated to determine the outcome of analysis.

**Winning Probabilities versus Probability Distributions**

In each selection round of the MC-MCDM analysis, a deterministic problem with randomly selected performance measures is evaluated using the definition of optimality provided by the corresponding MCDM method. The results of all deterministic problems should be aggregated at the end of analysis to form unique indices for evaluating the goodness of alternatives. Results of each analysis round can be evaluated and stacked up in two different ways, each providing different insights into the problem.

When the decision-maker is concerned with finding out the most probable optimal solution of the problem, the winning probabilities of all alternatives should be calculated. In order to do so, the optimal solution in each round of random selection will be identified using the considered MCDM method. At the end of analysis, the winning probabilities can be calculated by dividing the number of times each alternative has been identified as the winner to the total number of iterations. Ranking alternatives according to this index implies that an option is better if it has a higher probability to be the optimal solution of the problem. In this case, only the
winner of each deterministic MCDM problem will be recorded. Thus, the overall results only indicate the probability for being first in the overall ranking. The best alternative is the most probable one to become the winner; the second best alternative is the second most probable option to become the winner and so forth. However, in this case, results do not provide further information about the performance of alternatives when they are not the winner. As an example, when alternative A with the highest winning probability X % it is selected as the optimal solution of the problem. However, no information is provided regarding the 1-X % of the times that A is not the best alternative. Thus, the decision-maker does not know where A might rank when it is not the best solution. This study argues that such information should be provided to the decision-maker as it can affect the decision making process. For example, if the decision-maker learns that the alternative A is ranked as the worst option 1-X % of the times (when it is not the winner) he might consider A as a risky option and does not select it even if it has the highest winning probability among the available alternatives.

To rectify this problem and inform the decision-maker about the reliability of each alternative, the probabilities of being ordered at different ranks can be calculated for each alternative. In order to calculate ranking distributions, in each round of random selection, the rankings of all alternatives are recorded. By recording rankings through the entire analysis, the probability that an alternative takes a specific rank can be calculated by dividing the total number of times the option is placed at a given rank to the total number of iterations.

Ranking distributions provide valuable information to the decision-makers and help them better understand the risks associated with selection of each alternative. Some of the common ranking distributions are presented in Figures 3 through 5 to help facilitating ranking distribution.
results in MC-MCDM problems. In the first case (Figure 3), probable ranks for the alternative are concentrated around a single position (rank 2) in the overall ranking. This type of distribution might be considered more desirable since the decision-maker is faced with a lower level of risk (higher reliability). But, in the second case (Figure 4) probable ranks are highly dispersed. This indicates a higher level or risk (lower reliability) associated with the alternative as when the alternative does not perform as the best one, it becomes the worst alternative in most cases. A higher risk is associated with larger distance between possible ranks because, for different values within the feasible performance space, the rank of the alternative could change drastically. Figure 5 shows another undesirable ranking distribution when the alternative is almost equally probable at all ranks.

Figure 3 Ranking distribution type A
It should be noted that the final decision based on probability distributions depends on the judgment and risk attitude/tolerance of decision-makers. Therefore, a unique approach or a dominant strategy cannot be proposed for making the best decision based on ranking probability.
distributions. Nevertheless, consideration of ranking distributions is necessary to make a reliable decision in different decision making conditions.

**Robustness of Decision and the Risk Attitude of the Decision-maker**

Decision making based on ranking distributions is not a straightforward procedure, especially when the most probable optimal solution is not the most reliable one. In such case, a decision-maker might try to select the next best option with a higher probability of being ranked at higher positions (more reliability). Figure 6 shows hypothetical ranking distributions for four alternatives. Alternative A is the most probable optimal solution of the problem since it has the highest winning probability. However, it has a type B ranking distribution (Figure 4). This alternative performs better than others in fifty percent of the times, but it is the worst alternative in most other situations. A risk-taker decision-maker might accept the risk associated with alternative A while a risk-averse decision maker might prefer to select alternative B, which can be considered as a more reliable alternative. Although B is the second most probable optimal solution of the problem, it is never ranked as the worst alternative.
Convergence of Results

The suggested MC-MCDM method is an iterative process and the procedure should be repeated enough times to ensure that not only all the points within the performance regions are included in the analysis, but also all possible combinations of alternatives’ performances have been considered. To ensure that the number of iterations have been sufficient to fully capture the characteristics of the problem, convergence of the results can be controlled. In early stages of the analysis winning probabilities of the alternatives could fluctuate drastically. But, for a large enough number of iterations these probabilities should approach a constant value. Therefore, controlling the trend of winning probabilities can determine the sufficiency of iterations. The control procedure can be better explained using a simple decision making example, characterizes
in Table 2. Figure 7 shows how the winning probabilities of the three equally good alternatives converge over time to a same value. This figure shows that the winning probabilities reach a steady state after 700 iterations.

Table 2 Performance values of different alternatives under two different criteria in a sample problem

<table>
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<th>Criterion 1</th>
<th>Criterion 2</th>
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<tr>
<td>Alternative 1</td>
<td>[0,100]</td>
<td>[0,100]</td>
</tr>
<tr>
<td>Alternative 2</td>
<td>[0,100]</td>
<td>[0,100]</td>
</tr>
<tr>
<td>Alternative 3</td>
<td>[0,100]</td>
<td>[0,100]</td>
</tr>
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</table>

Figure 7 Changes in winning probabilities of the alternatives in the sample problem with number of iterations

Different characteristics of the problem can alter the number of required cycles for convergence of results, e.g., number of alternatives and criteria, length of the performance ranges (intervals); and their relative placement. In this study, the required number of selection rounds is
estimated visually, through controlling the convergence of ranking probabilities. However, the relation of standard deviation of the results with the number of repetitions can be mathematically examined to determine the minimum (optimum) number of required random selections.
CHAPTER 4: THE GROUP DECISION SUPPORT SYSTEM (GDSS) SOFTWARE PACKAGE

Introduction

As discussed in previous chapters, during an MC-MCDM analysis the stochastic problem is mapped into numerous deterministic ones using a Monte-Carlo selection procedure. Then, the deterministic problems are analyzed and the results are aggregated, led by calculation of winning probabilities and ranking distributions of the options. These calculations depend on the selected MCDM rule. Nevertheless, the overall of MC-MCDM procedure for calculating winning probabilities or ranking distribution is the same. This procedure is presented in Figure 8.

To facilitate the application of suggested MC-MCDM method to stochastic decision making problems, a software package, named Group Decision Support System (GDSS), was developed in this study. Following the overall procedure presented in Figure 8, GDSS includes a Monte-Carlo selection module that creates deterministic data sets from stochastic input data and sends them to subroutines for the MCDM analysis. These subroutines have been developed for five different MCDM methods (i.e., Lexicographic, Maximin, Dominance, SAW, and TOPSIS) based on theoretical background discussed in Chapter 2. This chapter presents the user interface and the different features of GDSS.
Figure 8 The overall procedure for application of the MC-MCDM method

**Input data**

Figure 9 shows the user interface for the data entry tab. Number of criteria, alternatives and performance measures can be determined in this tab. Deterministic performance measures must be entered as single numbers while stochastic payoffs have to be entered as intervals representing the possible performance ranges of alternatives. The current version of GDSS can
only handle uniformly distributed performance ranges. However, required fields for selection of other distribution functions have been considered that will be operative in future versions.

![User interface of the data entry tab in GDSS](image)

Figure 9 User interface of the data entry tab in GDSS

In addition to MCDM methods, two other categories of decision-analysis rules, namely, Social Choice (Voting) Rules (Sheikhmohammady and Madani, 2008a; Shalikarian et al., 2011) and Fallback Bargaining methods (Sheikhmohammady and Madani, 2008a; Madani et al., 2011; Brams and Kilgour, 2001) have also been included in GDSS. As will be discussed in a later part of this chapter, most of these methods require ordinal preference of alternatives under each criterion. Therefore, different ranking strategies (i.e. standard competition ranking, modified competition ranking, dense ranking and fractional ranking) have been considered and included in
GDSS to arrange the preference order of alternatives under each criterion based on their performances.

**Monte-Carlo selection**

Stochastic input data are available in intervals, representing the possible performance ranges. The Monte-Carlo selection subroutine generates random numbers within these intervals. In each round of selection a random number from each stochastic performance range is selected to generate a temporary deterministic decision matrix that can be analyzed using different MCDM methods. The general Monte-Carlo selection procedure is presented in Figure 10.

Figure 10 Monte-Carlo selection procedure
The user interface of the Monte-Carlo selection tab (Figure 11) has several fields for controlling different variables of analysis. The user can set the number of random selection cycles. The user should also select the desired output format (i.e., winning probabilities or ranking distributions). This selection would alter the recording type and aggregation procedure of MCDM results in each selection round. The user also needs to select the desired weighting method (Entropy method or user defined weights) and the MCDM rule using the Monte-Carlo selection tab.

![Figure 11 User interface of the Monte-Carlo selection tab](image-url)
Maximin

The Maximin subroutine has been developed based on the theoretical basis of the Maximin rule, explained in Chapter 2. The Monte-Carlo selection subroutine sends deterministic input data to the Maximin subroutine. Once the analysis is done, results are sent back to the Monte-Carlo selection subroutine for update. Figure 12 shows the overall procedure for Maximin decision making. Once the number of iterations reaches the cycles number, set by the user, results are reported to the user as shown in Figure 13. The best alternative based on this method is highlighted in the user interface to facilitate reading the results.

Figure 12 Overall procedure of decision analysis based on the Maximin method
Similar to the Maximin subroutine the Dominance subroutine receives deterministic input data from the Monte-Carlo selection subroutine and sends the results back to this subroutine for updating and recording the overall results. Figure 14 shows the step-by-step procedure for decision analysis based on the Dominance rule. Once the analysis is complete the user can see the results of the analysis based on the Dominance rule through the Dominance results tab of GDSS (Figure 15).
Figure 14 Overall procedure of decision analysis based on the Dominance method

Figure 15 User interface of the Dominance results tab
Lexicographic

Unlike Maximin and Dominance, the Lexicographic method requires criteria weighting. Therefore, in Lexicographic and Monte-Carlo tabs (for deterministic or stochastic analysis, respectively) separate fields have been assigned, so that the user can select the proper weighting method. Criteria weights can be determined directly by the user or using the values of decision matrix through the Entropy Weighting Method (Zou et al., 2006; Mokhtari et al., 2012). Figure 16 shows the step-by-step procedure of deterministic decision analysis based on the Lexicographic method. Once the communication between the Monte-Carlo selection and Lexicographic subroutines is over and the decision analysis is completed, the user can see the results of the Lexicographic analysis through the Lexicographic results tab of GDSS (Figure 17).

Figure 16 Overall procedure of decision analysis based on the Lexicographic method
The TOPSIS subroutine receives deterministic data and criteria weights to find the optimal solution for the problem. The results of analysis will be sent back to the calling routine for display or recording, depending on the problem type (deterministic or stochastic). The step-by-step alternative ranking procedure through TOPSIS and the TOPSIS results tab of GDSS are presented in Figures 18 and 19, respectively.
Figure 18 Overall procedure of decision analysis based on the TOPSIS method

Figure 19 User interface of the TOPSIS results tab
Like Lexicographic and TOPIS methods, SAW requires weighting of alternatives along with a deterministic decision matrix to identify the optimal solution. The step-by-step alternative ranking procedure through SAW and the SAW results tab of GDSS are presented in Figures 20 and 21, respectively.

Figure 20 Overall procedure of decision analysis based on the Simple Additive Weighting (SAW) method
Other Decision Analysis Methods

Following the works of Madani et al. (2011) and Shalikarian et al. (2011), two other categories of decision analysis namely, Fallback Bargaining methods and Social Choice Rules have also been included in the GDSS to analyze stochastic multi-participant decision making problems. Here, a brief description of these methods along with their user interfaces in GDSS is presented.

Fallback Bargaining (FB) methods aim to maximize the minimum satisfaction of all stakeholders. FB methods simulate negotiations in which parties start bargain over their most preferred alternatives and fallback till they reach an agreement. Detailed introduction to different

Social Choice Rules (SCR) or voting rules, on the other hand, aim to find the socially optimal solution, which satisfies the preferences of all stakeholders to the possible extent (sheikhmohammady et al., 2010). SCRs are based on voting concepts. Decision-makers vote for alternatives based on their preference order. Then, votes are aggregated according to a given voting rule to identify the socially optimal solution based on that voting rule. Details of these methods can be found in Sheikhmohammady and Madani (2008a) and Shalikarian et al. (2011).

Multi-Attribute Single-Decision Maker problems can be analyzed using FB methods or SCRs, by assuming that criteria represent different stakeholders. It should be emphasized that although, SCRs and FB methods do not require criteria weighting, they can only handle ordinal input data. In GDSS, the subroutine that converts cardinal data to ordinal preferences will rank alternatives under each criterion according to their payoffs and the preference orders will be sent to SCR or FB subroutines for decision analysis. Two different tabs in the GDSS, include the SCRs and FB methods. Each tab contains several sub-tabs for selecting different SCRs and FB methods. The Social Choice Rules tab includes Condorcet Choice rule, Borda scoring, Plurality rule, Anti-Plurality rule, Median Voting rule, Hare System of voting, Majoritarian Compromise, and Condorcet Practical method; and the Fallback Bargaining tab includes Unanimity, Q-Approval and Fallback bargaining with Impasse methods. The user interfaces of GDSS for these methods are presented in Figures 22 and 23.
Figure 22 User interface of Social Choice Rules

Figure 23 User interface of Fallback Bargaining methods
CHAPTER 5: MC-MCDM APPLICATION TO CALIFORNIA’S SACRAMENTO-SAN JOAQUIN DELTA PROBLEM

Introduction

Providing water to more than 22 million people, and serving as a unique habitat of several endangered species and a major component of the states' civil infrastructure, the Sacramento-San Joaquin Delta is the heart of water supply system and a major support of California's trillion dollar economy and 27 billion dollar agriculture (CA DWR, 2008). The Delta is a web of 57 reclaimed islands and 700 miles of channels at the intersection of two of California's largest rivers. There are more than six counties in the Delta and five rivers flowing into it that altogether with their tributaries collect 45% of the state's runoff (Lund et al., 2007). Due to a special formation process, the Delta has a rich and productive soil. Thus, settlers began farming in this region shortly after the gold rush. Since the Delta is a low land, to protect farmlands from floods, levees have been built along the water channels. Today, most of the 1,150 square miles of Delta's area, laying 20 feet or more below surrounding water, is still reclaimed by such levees (Ingebritsen et al., 2000). Due to increasing agricultural and domestic water demands of southern California, the Bay Area, and the San Joaquin valley, several aqueducts were built at the southern end of the Delta from 1930 to 1960 (Lund et al., 2008). Nowadays, not only the neighboring area, but most of the California's is dependent on the water provided by the Delta (CA DWR, 2008). Passage of electricity and gas transmission lines and some major state highways through the Delta along with presence of several busy ports and natural gas extraction facilities, makes the Delta an important component of California's
infrastructure (Ingebritsen et al., 2000; Madani and Lund, 2012). Moreover, the Delta is a natural habitat for more than 500 wild species, 20 of which recognized endangered such as the Delta Smelt or Chinook salmon (CA DWR, 2008).

Over decades, the increasing demands of competing sectors and decreasing water quality along with vulnerability of the Delta to rising sea level and natural disasters such as earthquakes, have put the Delta's ability to meet the water demands in jeopardy, threatening the viability of the region. The economic cost of a very possible failure due to an earthquake or other natural disasters can be up to 40 billion dollars in five years together with water export cut off for several months and disruption of power and road transmission lines (Lund et al., 2007). The Delta water quality is another major concern. Serving as a drainage area for agricultural, domestic and industrial runoffs over the past decades along with permeation of saltwater into the Delta, have led to alarming deteriorating water quality in the region (Lund et al., 2007). Moreover, drastic decline in wildlife and high extinction risk of endangered species have caused serious dissatisfaction of the environmentalists (CA DWR, 2008).

A detailed research on Delta’s current situation and long-term solutions for the emerging crisis has been carried out by Lund et al. (2007). In their research nine feasible long-term solutions were evaluated, considering different environmental and economic criteria. Among the nine solutions, four were suggested for further investigation. These four alternative solutions are: (1) continuing the current water exports through the existing facilities (business as usual); (2) building a canal, tunnel, or pipeline to convey water around the delta (tunnel); (3) combination of the two previous strategies (dual conveyance); and (4) ending water exports (stop exports). These four scenarios were further investigated by Lund et al. (2008) based on two major criteria, i.e.,
the average cost and viability of fish population (fish survival rate). Results of this assessment are presented in Table 3.

Table 3 Estimated Performance Ranges (Lund et al., 2008)

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Economic cost (B$/year)</th>
<th>Fish survival (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business as usual (BAU)</td>
<td>0.55-1.86</td>
<td>5-30</td>
</tr>
<tr>
<td>Tunnel (T)</td>
<td>0.25-0.85</td>
<td>10-40</td>
</tr>
<tr>
<td>Dual conveyance (DC)</td>
<td>0.25-1.25</td>
<td>10-40</td>
</tr>
<tr>
<td>Stop exports (SE)</td>
<td>1.25-2.5</td>
<td>30-60</td>
</tr>
</tbody>
</table>

Madani and Lund (2011), proposed a non-cooperative game theoretic approach for modeling the Delta’s multi-criteria multi-decision maker problem (Table 3) with four alternatives and two decision makers using a Monte-Carlo selection method for dealing with the uncertainty involved (performances are not unique numbers). Essentially, the problem is a stochastic decision making problem due to uncertain performances. Based on their suggested method, the stochastic problem was converted to numerous deterministic decision making problems through a Monte-Carlo selection. Assuming that each deterministic problem corresponds to a specific game structure, they used various non-cooperative game theory solutions (Madani and Hipel, 2011) to identify the best water export option. Their results suggested that the current water export strategy (BAU) is a likely option under non-cooperation (current condition) and once the parties decide to cooperate, building a tunnel (T) becomes the most likely option. They identified dual conveyance (DC) as the second most likely water export strategy under cooperation. Madani et al. (2011) studied the same problem using a bargaining approach. In their approach, the decision making problem was modeled as a game in which
parties bargain until a consensus is developed and one strategy is selected. Similarly, selection of a tunnel and dual conveyance were identified as the likely outcomes of the bargaining process. While the general findings of the two studies match, the winning probabilities of the alternatives were not equal, showing the sensitivity of the findings to the applied selection rules. While the difference may not be significant for small decision making problems, in larger problems inconsistencies could become important. Shalikarian et al. (2011) used a different approach for modeling the Delta decision making problem. Instead of assuming that decisions are made in a non-cooperative environment, in which parties may compete sometimes to increase their personal gains, they considered the problem as a social decision making problem (with medium cooperation level) in which parties can simply vote and rank the alternatives based on their different perspectives. The final decision is made based on the social choice or voting rules. While the results obtained based on voting rules may not be necessary optimal from the systems perspective, they are socially optimal. Application of the social choice rules to the Delta decision making problem also suggested that building a tunnel is the socially optimal solution, followed by the dual conveyance as the second socially optimal solution. The estimated selection probabilities of the alternatives based on social choice rules were different from the results of the two previous studies, highlighting the importance of using appropriate rules for solving decision making problems. Rastgoftar et al. (2012) used a stochastic fuzzy approach to identify the best solution for the Dealt problem. Integration of Monte-Carlo selection and Fuzzy decision analysis in their study provided a framework for analyzing decision making problems with random (uncertain) and ambiguous (fuzzy) input parameters. In this study, the stochastic problem was converted into numerous deterministic ones through Mont-Carlo selection, first. Each
deterministic problem then was analyzed using fuzzy decision making methods, assuming deterministic triangular membership functions for the fuzzy data. Based on their results, building a tunnel is the best solution for the Delta problem and a dual conveyance approach is the second best option. According to the results of this stochastic fuzzy method, stopping the water export from the Delta (SE) is a better solution than continuing the current trend (business as usual).

To further investigate the effects of the choice of decision making rule on the final results of Multi-Criteria Multi-Decision maker problems, this study uses the conventional Multi-Criteria Decision Making (MCDM) methods rooted in Operations Research (OR) to solve the Delta decision making problem as a benchmark example. In most of the OR-based MCDM methods, a single, all-powerful decision maker determines the fairest alternative considering all the objectives of different decision makers (Madani and Lund, 2011). In this chapter, five well-known MCDM methods namely, Dominance, TOPSIS, SAW, Lexicographic, and Maximin are used to prescribe the optimal solution to the Delta decision making problem from the central (social) planner’s perspective. Generally, prescriptive methods assume that all the stakeholders are compliant to the fair and unbiased decision maker while methods such as non-cooperative game theory and fallback bargaining are more descriptive, trying to describe the procedure of negotiations with emphasis on self-optimizing behavior of the players (Madani, 2010; Madani and Lund, 2011).

**MC-MCDM Analysis**

To deal with the uncertainty involved (the payoff of each alternative can be any number within the given intervals in Table 3), the suggested Monte-Carlo Multi-Criteria Decision
Making (MC-MCDM) procedure has been followed. Based on the suggested method, GDSS converted the stochastic decision making-problem to numerous deterministic problems and solved them based on different MCDM methods. The number of iterations was set to 100,000 rounds of selection, and the convergence check showed that 100,000 iterations are sufficient for convergence. The following sections present and discuss the results obtained from the GDSS package for the Delta decision making problem based on MCDM methods.

**Lexicographic**

The winning probabilities of the four proposed Delta solution alternatives based on the Lexicographic method are presented in Tables 3. Based on winning probabilities, building a tunnel (T) is the best solution, followed by the dual conveyance (DC). The overall ranking of the four solutions based on this method is as follows:

Tunnel > Dual conveyance > Stop export > Business as usual

Table 4 Winning probabilities of alternatives (in percent) based on the Lexicographic method

<table>
<thead>
<tr>
<th>Alternative</th>
<th>BAU</th>
<th>T</th>
<th>DC</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning probabilities</td>
<td>3.361</td>
<td>66.702</td>
<td>29.496</td>
<td>0.441</td>
</tr>
</tbody>
</table>
Reliability of Tunnel as the solution to this problem can be evaluated using the ranking distributions of alternatives, shown in Figure 24. Based on this figure, ranking distributions of the alternatives are mostly concentrated around a single position (type A ranking distribution), reflecting the high reliability of the overall ranking. Therefore, T is a reliable best solution to the problem.

Simple Additive Weighting (SAW)

Table 4 indicates the winning probabilities of the alternatives under the SAW method. These probabilities follow the same trend as estimated probabilities based on the Lexicographic method (Table 3). Based on winning probabilities, Tunnel is the social planner’s solution of the problem. Ranking distributions of the alternatives (Figure 25) show a high reliability of this solution. The overall ranking of the four solutions based on the SAW method is as follows:
Tunnel > Dual conveyance > Stop export > Business as usual

Table 5 Winning probabilities of alternatives (in percent) based on the SAW method

<table>
<thead>
<tr>
<th>Alternative</th>
<th>BAU</th>
<th>T</th>
<th>DC</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning probabilities</td>
<td>2.793</td>
<td>67.338</td>
<td>29.561</td>
<td>0.258</td>
</tr>
</tbody>
</table>

Figure 25 Ranking distributions of alternatives based on the SAW method

**TOPSIS Method**

Application of the TOPSIS method to the Delta decision making problem yields the results showed in Table 5 and Figure 26. The winning probabilities are similar to the estimated probabilities based on the two previous methods. TOPSIS also selects Tunnel as the best and reliable alternative. The overall ranking of the four solutions based on this method is:

Tunnel > Dual conveyance > Stop export > Business as usual
Table 6 Winning probabilities of the alternative (in percent) based the TOPSIS method

<table>
<thead>
<tr>
<th>Alternative</th>
<th>BAU</th>
<th>T</th>
<th>DC</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning probabilities</td>
<td>2.781</td>
<td>67.130</td>
<td>29.833</td>
<td>0.256</td>
</tr>
</tbody>
</table>

Figure 26 Ranking distributions of alternatives based on the TOPSIS method
Maximin

Winning probabilities of the alternatives and their ranking distributions based on the Maximin method are presented in Table 5 and Figure 27, respectively.

Table 7 Winning probabilities of the alternative (in percent) based the Maximin method

<table>
<thead>
<tr>
<th>Alternative</th>
<th>BAU</th>
<th>T</th>
<th>DC</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning probabilities</td>
<td>6.358</td>
<td>48.929</td>
<td>44.648</td>
<td>0.065</td>
</tr>
</tbody>
</table>

The overall ranking of the alternative based on the Maximin method is as follows:

Tunnel > Dual conveyance > Business as usual > Stop exports

This ranking is different from the consistent rankings based on the previous three methods. While the other three methods suggest that the current water export strategy (BAU) is inferior to all other three solutions, the Maximin method suggests BAU as a better option than stopping the water exports (SE). This is due to the conservative nature of the Maximin method, which finds SE prohibitive due to the high cost of this solution. The calculated ranking distributions based on this method (Figure 27) are also very different from the same based on the other three methods. Based on the Maximin method, building the tunnel is slightly preferred to the dual conveyance option.
Dominance method’s results are presented in Table 7 and Figure 28. These results are different from the results of the previous methods. It should be noted that unlike other cases, the summation of winning probabilities of the alternatives is more than 100% in case of the Dominance method due to the possibility of ties. Dominance also finds Tunnel as the best and reliable solution of the social planner to the Delta problem. The overall ranking of the alternatives is consistent with the ranking orders found under most of previous methods:

Tunnel > Dual conveyance > Stop exports > Business as usual
Table 8 Winning probabilities of the alternative (in percent) based on the Dominance method

<table>
<thead>
<tr>
<th>Alternative</th>
<th>BAU</th>
<th>T</th>
<th>DC</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning probabilities</td>
<td>10.816</td>
<td>72.246</td>
<td>53.953</td>
<td>13.122</td>
</tr>
</tbody>
</table>

Figure 28 Ranking distributions of the alternatives based on the Dominance method

Comparison with Previous Studies

The results of the analysis based on the five different MCDM methods used in this study are summarized in Table 8. All these social planner methods suggest building a tunnel (T) as the optimal solution to the Delta problem and development of a dual conveyance (DC) system as the second best option. While four of the applied MCDM methods suggest that continuation of the water exports (BAU) is the worst strategy, Maximin (the most conservative method) suggests that this strategy as a better option than ending the water exports (SE) completely due to the high economic costs of SE despite its significant environmental benefits.
Table 9 Summary of GDSS results based on the MC-MCDM method

<table>
<thead>
<tr>
<th>MCDM Methods</th>
<th>Preference Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lexicographic</td>
<td>T &gt; DC &gt; SE &gt; BAU</td>
</tr>
<tr>
<td>SAW</td>
<td>T &gt; DC &gt; SE &gt; BAU</td>
</tr>
<tr>
<td>TOPSIS</td>
<td>T &gt; DC &gt; SE &gt; BAU</td>
</tr>
<tr>
<td>MAXIMIN</td>
<td>T &gt; DC &gt; BAU &gt; SE</td>
</tr>
<tr>
<td>Dominance</td>
<td>T &gt; DC &gt; SE &gt; BAU</td>
</tr>
</tbody>
</table>

Table 10 compares the overall ranking of the four considered alternatives using four different approaches, namely the stochastic game theoretic approach (Madani and Lund, 2011), the stochastic bargaining approach (Madani et al., 2011), the stochastic voting approach (Shalikaran et al., 2011), and the stochastic MCDM approach (this study). The differences between the results suggest that the final results of stochastic multi-participant decision making problems can be sensitive to the choice of the decision analysis method. Although, the differences between the results may not be significant for a small problem like the Delta problem, such differences become more important for more complex decision making problems. This highlights the importance of selecting the most appropriate analysis method that better reflects the reality of decision making problem. In case of participation of multiple stakeholders, MCDM (social planner) and social choice decision making methods may not be appropriate for analyzing the decision making problem as these methods are not descriptive. Game theory and fallback bargaining methods seem more reliable for analyzing such situations. On the other hand, descriptive methods may fail to provide the best solutions when in practice the central planner has the authority to implement the solution. In case of the Delta problem, if California is the single decision maker to select and implement the solution, Tunnel is the best solution.
Table 10 Comparison of the results of different stochastic decision analysis methods applied to the Delta problem as a benchmark example

<table>
<thead>
<tr>
<th>Category</th>
<th>Method</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Game theory approach</strong></td>
<td>Weak equilibrium</td>
<td>BAU&gt;T&gt;DC&gt;NE</td>
</tr>
<tr>
<td>(Madani and Lund, 2011)</td>
<td>Strong equilibrium</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td><strong>Fall-Back bargaining methods</strong></td>
<td>Unanimity FB</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td>(Madani et al., 2011)</td>
<td>1-Approval FB</td>
<td>SE&gt;T&gt;DC&gt;BAU</td>
</tr>
<tr>
<td></td>
<td>2-Approval FB</td>
<td>T&gt;DC&gt;BAU=SE</td>
</tr>
<tr>
<td></td>
<td>FB with impasse</td>
<td>T&gt;DC&gt;BAU=SE</td>
</tr>
<tr>
<td><strong>Social choice rules</strong></td>
<td>Borda score</td>
<td>T&gt;DC&gt;SE=BAU</td>
</tr>
<tr>
<td>(Shalikarian et al., 2011)</td>
<td>Condorcet choice</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td></td>
<td>Plurality rule</td>
<td>SE&gt;T&gt;DC&gt;BAU</td>
</tr>
<tr>
<td></td>
<td>Median voting rule</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td></td>
<td>Majoritarian compromise</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td></td>
<td>Condorcet practical</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td><strong>Stochastic fuzzy method</strong></td>
<td>Monte-Carlo fuzzy</td>
<td>T&gt;DC&gt;SE&gt;BAU</td>
</tr>
<tr>
<td>(Rastgoftar et al., 2012)</td>
<td>(centroid defuzzification)</td>
<td></td>
</tr>
<tr>
<td><strong>MCDM methods</strong></td>
<td>Lexicographic</td>
<td>T&gt;DC&gt;SE&gt;BAU</td>
</tr>
<tr>
<td></td>
<td>SAW</td>
<td>T&gt;DC&gt;SE&gt;BAU</td>
</tr>
<tr>
<td></td>
<td>TOPSIS</td>
<td>T&gt;DC&gt;SE&gt;BAU</td>
</tr>
<tr>
<td></td>
<td>MAXIMIN</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
<tr>
<td></td>
<td>Dominance</td>
<td>T&gt;DC&gt;BAU&gt;SE</td>
</tr>
</tbody>
</table>
CHAPTER 6: SUMMARY AND CONCLUSIONS

This study aimed to introduce a new decision making approach based on Monte-Carlo selection to improve multi-participant multi-criteria decision making under uncertainty. MCDM methods were suggested as reliable social planner methods for single-participant decision making or fully cooperative multi-participant decision making. The suggested MC-MCDM method, maps a stochastic problem to numerous deterministic ones through a random selection procedure and solves them using different MCDM methods. Recording the winners of deterministic problems, alternatives’ winning probabilities are calculated to identify the most probable optimal solution of the problem. Ranking distributions (the probabilities of being ordered at different ranks) are also calculated to evaluate the risk associated with ranking of different alternatives. It was argued in this study that depending on the risk attitude of decision-makers, a solution other than the most probable optimal might be selected to avoid the high risk associated with the best solution, which has an undesirable ranking distribution.

Unlike most other methods, proposed in former studies (e.g. Triantaphyllou and Sanchez, 1997; Barron and Schmidt, 1988; Janssen, 1996; Hyde, 2006; Butler et al., 1997), the suggested MC-MCDM approach does not provide a definitive answer to stochastic problems. Instead, it maps the uncertainty from input data to the analysis results to inform the decision-maker about the possible risks associated with the results. Application MC-MCDM method is not limited to a certain type of optimality concepts, tested in this study, and the suggested procedure can be performed using most MCDM methods. While in this study, probability distributions of the input
data were considered to be uniform, the suggested random selection procedure can be based on other probability distributions in future studies.

In order To facilitate the application of MC-MCDM method in practice, the Group Decision Support System (GDSS) software package was developed in this study, which lets ordinary users with limited knowledge of decision making methods, obtain a range of results in a very short time. With a user-friendly interface, this software facilitates multi-criteria decision making under uncertainty with single or multiple participants. Following the introduction of a decision making problem to GDSS (first data entry step) and setting the number of iterations, users can select their desired decision analysis methods. Different classes of decision analysis methods, namely MCDM, Social Choice Rules, and Fallback Bargaining, have been included in this GDSS to enrich its capabilities in providing reliable results to group decision making problems with different levels of cooperation among the decision-makers. MCDM methods are appropriate for decision making problems with a single decision maker or with multiple fully cooperative decision makers; Social Choice rules are appropriate for group decision making with medium level of cooperation; and Fallback Bargaining methods are suitable for group decision making problems with low cooperation level among the parties. By evaluating the results under different class of decision making methods, the user can evaluate the sensitivity of the decision making solution to the cooperation level among the decision-makers. The user-friendly interface of the GDSS facilitates interaction of user with the software, even when the user is not fully aware of the mathematical details of the decision making methods. Obtaining the results under a range of methods under each class increases the robustness of findings and minimizes the sensitivity of results to different notions of optimality, fairness, and stability.
The efficiency of the suggested MC-MCDM method in dealing with real-world problems was evaluated using the California’s Sacramento-San Joaquin Delta problem, as a simple benchmark MCDM problem. GDSS was used to apply the MC-MCDM method to calculate the winning probabilities and find the ranking distributions of four alternative solutions of the Delta problem, i.e. business as usual, building a tunnel for conveying water around the delta, a dual conveyance and stop export of water. Interpretation of the results determined that building a tunnel is the best social planner solution with a relatively high reliability. The results of this study were compared to findings of former studies that had applied other methods to solve the Delta benchmark problem. The comparison suggests that the ranking of alternatives in this problem is sensitive to the choice of method and/or level of cooperation among the decision-makers. It should be emphasized that in absence of a central power (unique all-powerful decision maker) that can implement the best solution regardless of stakeholders’ preference, normative methods such as MCDM methods or Social Choice Rules may not provide a practical solution to the problem. Descriptive methods like Fallback Bargaining or Game theory methods are more proper in such situations. In case of the Delta problem, MCDM results are useful if conflicting parties agree to implement the social planner’s solution or a superpower (e.g. California) tries to intervene and implement a solution.
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