Chapter 2

Decision Support Systems

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.79390

Abstract

The current decision-making problems is more complex than it was in the past, prompting the need for decision support. Most real-world decision-making situations are subject to bounded rationality; whereby the technical and economic evaluation of all solution alternatives (branches) is bounded by the consideration of dominant subjective constraints. The early definition of DSS introduced it as a system that intended to support decision makers in semi-structured problems that could not be completely supported by algorithms. DSSs were planned to be an accessory for managers to expand their capabilities but not to replace them. Decision support systems could provide the means to complement decision makers by quantitatively supporting managerial decisions that could otherwise be based on personal intuition and experience. In addition to the traditional DSS characteristics (i.e., data and model orientation, interactivity), the inclusion of an intelligent knowledge base would be required to quantify the impacts of both technical (hard) and subjective (soft) constraints.

Keywords: decision support system, decision analysis, decision alternatives, criteria, weight

1. Introduction

As a matter of fact, nowadays, decision-making is more complicated than it was in the past for two governing reasons. Firstly, growing technology and communication systems have spawned a greater number of feasible solution alternatives from which a decision-maker can select. Secondly, the increased level of structural complexity of today's problems can result in a chain reaction of magnification of costs if an error should occur [1].

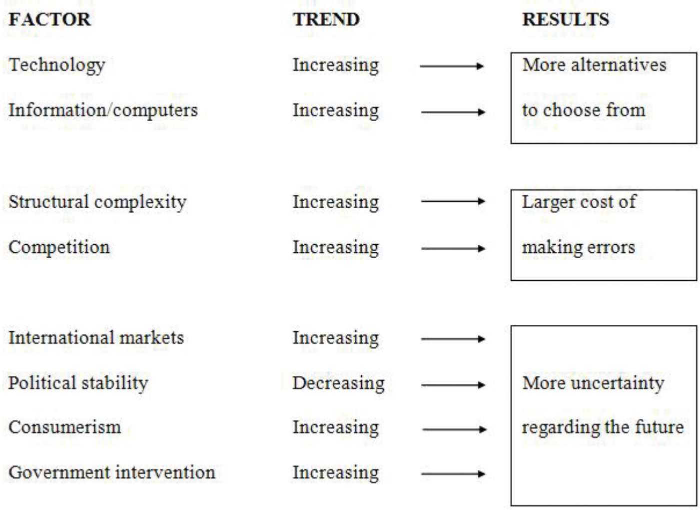

Figure 1. Factors affecting decision-making [2].

Turban and Aronson examined what they consider to be the major factors that affect decision-making, and have drawn conclusions regarding current trends and corresponding results/ impacts on decision-making (**Figure 1**) [2].

In general, managerial decisions are derived from human judgment which includes deductive reasoning supported by experience, information and knowledge [3]. To compensate the effect of human error, the decision-making process can be partially supplemented by computer aided automation. The final system cannot be fully automated, unless perfectly processed information and an optimum model is provided.

DSS is used to model human reasoning and the decision-making process; both are capable of accepting facts from users, processing these facts, and suggesting the solutions that are close to the solutions that are presented by human experts [4]. DSS can considerably support in evaluating different maintenance decisions in order to select the most robust and cost-effective answers in a systematic and transparent way [5].

The growing level of decision support system accomplishment in organizations over the recent decades is strong proof that DSS is a viable and well accepted managerial tool.

2. Decision support systems

2.1. A brief history

Over the past fifty-plus years, the field of Information Systems (IS) has undergone a considerable progression of growth. Each expansion has built on its predecessors and supplemented them in the process [6].

Before 1965, it was extremely expensive to build a large-scale information system. Around this time, the establishment of the IBM System 360 and other more powerful processor systems made it more practical and cost-effective to build management information systems (MIS) in large corporations. The pre-specified reports (e.g., budget, cumulative cost and progress statements) output from MIS are data-oriented and restrict decision-makers to gathering the necessary information for making choices, but do not supply a framework to model decision problems. At that point, it was recognized that technological support for decision-making must facilitate ad hoc (problem-specific) recovery of data and managerial control over model manipulation. Decision-makers did not wish to be locked into systems they could not control [7].

In the late 1960s, model-oriented DSS or management decision systems became practical. Two DSS pioneers, Peter Keen and Charles Stabell, stated the concept of decision support which was extracted from the theoretical studies of organizational decision-making during the late 1950s and early 1960s and the technical work on interactive computer systems that mostly carried out in the 1960s [8].

In 1961, Michael S. Scott Morton published "Management Decision Systems: Computer-Based Support for Decision Making." Later, in 1968–1969, he studied the effect of computers and analytical models in critical decision-making. His research played a "key role in launching the DSS movement" [9].

In 1980, Steven Alter published an important book titled "Decision Support Systems: Current Practice and Continuing Challenge." His research founded a structure for identifying management DSS [10].

Bonczek et al. established a theory based on knowledge-based DSS [11]. Their research presented how Artificial Intelligence and Expert System technologies were applicable to developing DSS. They also introduced four essential "aspects" or components of all DSS [12], these are:

1. A Language System (LS) which includes all the recognizable messages.
2. A Presentation System (PS) for all messages emitted by DSS.
3. A Knowledge System (KS) addressing all the imbedded knowledge in a DSS.
4. A Problem-Processing System (PPS) that tries to diagnose and solve problems.

In the early 1990, business intelligence, data warehousing and On-Line Analytical Processing (OLAP) software began expanding the potential of DSS [10]. Around 1997, the data warehouse became the cornerstone of an integrated knowledge environment that granted a higher level of information sharing, facilitating faster and better decision-making [13].

Decision support systems have experienced a noticeable growth in scholarly attention over the past two decades. In according to Google Scholar (October 2007), the rate has increased from less than three publications per week in 1980 to over 20 publications per day twenty-five years later [14]. The Internet and Web have also accelerated developments in decision support and have provided a new way of capturing and documenting the development of knowledge in this research area [10].

2.2. DSS definitions

According to Mora et al., the decision maker employs computer technology to: (a) organize the information into problem factors, (b) attach all the attributes to a model, (c) use the framework/model to simulate alternatives, and (d) select the best course of action [15]. The outcomes are reported as parameter conditions, experimental forecasts, and/or recommended actions. A typical architecture of DSS provided by Mora et al. is shown in **Figure 2** [15].

2.3. DSS ideal characteristics and capabilities

Defining standard characteristics of DSS is not viable but the major features that distinguish DSS from other previously established systems can be summarized from Turban and Aronson as follows [2]:

- DSS assists decision makers in semi-structured and unstructured problems (which cannot be solved by standard procedural methods or tools), employing human judgment and computers.

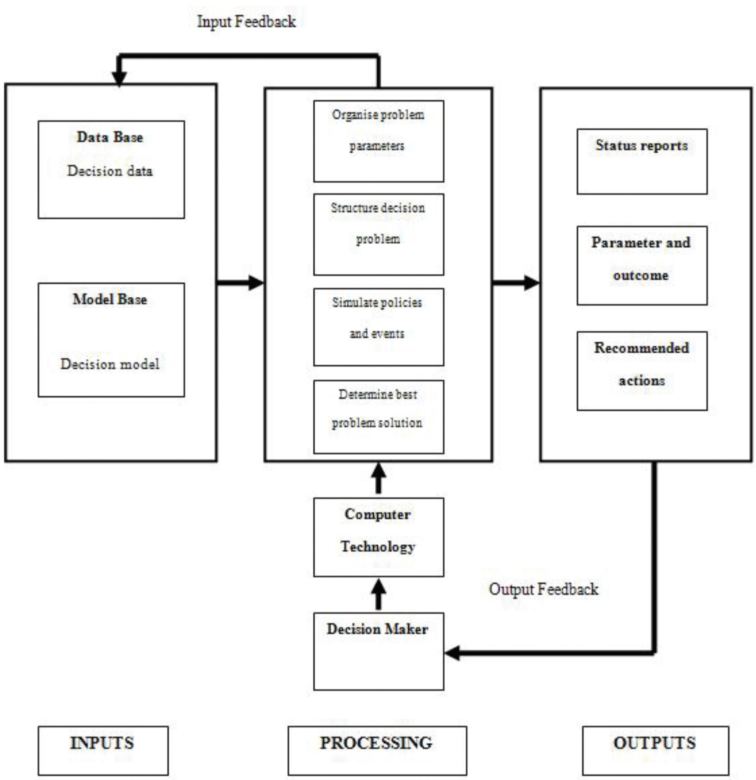

Figure 2. Typical architecture of decision support system (Mora et al., [15]).

- It covers a vast spectrum of managerial levels, from top executive to line managers.
- Support is provided to both individuals and groups. Less structured situations often require the intervention of several individuals from different divisions and organizational levels or sometimes even from different organizations.
- DSS facilitates several interdependent and/or sequential decisions that may be made once, several times, or repeatedly.
- DSS carries out all parts of the decision-making process: intelligence, design, choice and implementation.
- It covers a variety of decision analysis tools.
- DSS is adaptive and flexible, and so users can add, change, delete, or reorganize basic elements.
- DSS should be user friendly and have strong graphical interfaces.
- DSS tries to improve the effectiveness of decision-making (appropriateness and quality) rather than its efficiency (the cost of decision-making).
- DSS attempts to support the decision makers not to replace them. Therefore they will have control over all levels of the process.
- End users should be able to build (and modify) simple systems. Complicated systems can be constructed with assistance from information system (IS) experts.
- A DSS generally employs models for analysing problems since modeling enables experimenting with different strategies under different configurations.
- DSS should be able to supply access to a variety of data sources and formats.
- A DSS can be integrated with other systems and/or applications, and it can be distributed through networking and web technologies.

Figure 3 demonstrates an extension of an ideal set of DSS characteristics; based on the work of Turban and Aronson [2].

Lemass also emphasizes that a DSS should improve both the effectiveness and efficiency of decision-making [1]. Effectiveness is the degree to which identified goals are achieved, whilst efficiency is a measure of the application of resources to attain the goals. The effectiveness and efficiency of a DSS can be measured by its ability to enable decision-makers to:

- define difficult problems earlier;
- rapidly identify viable solutions;
- equitably compare the consequences of each solution;
- stylize an interface for displaying problem-specific (ad hoc) data collection and results presentation (e.g., tables, forms, graphics, etc.); and
- run sensitivity analyses to check model assumptions and hence help to defend proposed solutions more convincingly.

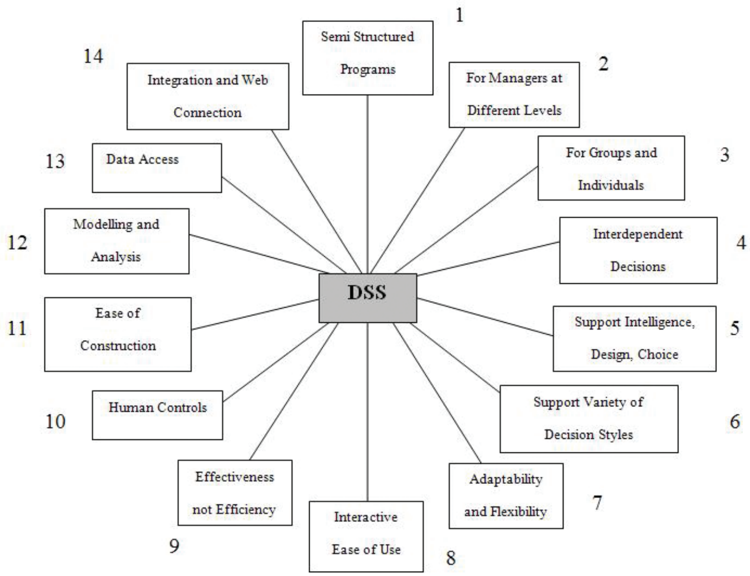

Figure 3. The desirable characteristics and capabilities of DSS.

3. An introduction to decision-making

Traditionally, a decision is defined as being a choice: a choice about a course of action [16], the choice of a strategy for action [17], a choice leading to a certain desired objective [18]. It can be clearly understood that decision-making as a non-random activity concluding in the selection of one course of action among multiple strategies and DSS is a prevailing system that can ease this process [6].

Simon stated that the process of making the decision includes three basic phases: intelligence, design, and choice [19]. Turban described how implementation, is also required over and above a "paper" solution, as the fourth phase, in order to solve the original problem [2].

The intelligence phase, or problem identification, involves gaining awareness that inconsistencies exist between the current state of a situation and the desired circumstances. At this level the decision maker tries to diagnose the problems that need to be addressed and/or opportunities that need to be tracked [20].

In the design phase, a decision maker attempts to generate alternatives, and analyses the options to provide knowledge about their relevant implications. During this phase, the decision maker may find that supplementary knowledge is required. This leads to a return to the intelligence stage to clarify the problems before continuing with the design activity [6].

During the choice phase, the decision maker selects one of the proposed alternatives that have been explored in the design phase. The outcome depends on the nature of the decision context and the decision maker's own traits and idiosyncrasies. It may be that none of the alternatives are satisfying (return to the design phase), that several competing alternatives gain high scores, or that the state of the context has changed dramatically after analysis of alternatives (return to the intelligence phase). However, one option must be chosen for implementation [21].

The fourth and final step is implementation. This phase includes a set of chosen solutions that need to be approved by stakeholders and put into action over time [20]. This requires cautious planning and sensitivity to those involved in the process and/or those affected by it. The resolution must then be monitored to guarantee that the problem has been corrected. If the problem has been rectified, then the decision-making procedure is finalized [22]. Generally, the outcome of successful implementation is solving the real problem while any failure results in returning to a former phase of the process [2].

3.1. The structure of decisions

There is a variety of decision types which can be classified based on specific factors. An appreciation of decision types can assist decision makers understand what knowledge and knowledge manipulation features would be required in decision support system [6]. The level of "programmability" or structuredness is a helpful aspect for understanding and classifying decisions. Simon argued that decisions could be placed along a spectrum from highly structured to completely unstructured [23]. Decisions may also be further classified as single-stage and multiple-stage, with either risk, certainty or uncertainty of outcome.

Structured decisions are made when well-known procedures can be readily applied to all the phases of decision-making to provide standard solutions for repetitive problems. They are characterized by definite decision criteria, a limited number of precise alternatives whose consequences can be worked out without any complexity [24].

Structured decisions	Unstructured decisions
Routine, repetitive	Unexpected, infrequent
Established and stable context	Emergent and turbulent contexts
Alternatives clear	Alternatives unclear
Implications of alternatives straightforward	Implications of alternatives indeterminate
Criteria for choosing well defined	Criteria for choosing ambiguous
Specific knowledge needs known	Specific knowledge needs unknown
Needed knowledge readily available	Needed knowledge unavailable
Result from specialized strategies (i.e., procedures that explicitly pre-specify full set of steps to follow in order to reach decisions)	Result from general strategies (e.g., analogy, lateral thinking, brainstorming, synthesis used in the course of reaching decisions)
Reliance on tradition	Reliance on exploration, creativity, insight, ingenuity

Table 1. Decision structuredness [6].

A semi-structured decision is made when some, but not all, of the phases of decision-making are structured. While some standard solution procedures may be applicable, human judgment is also called upon to develop decisions which tend to be adaptive in nature [1].

When none of the phases of decision-making are structured, the resulting decisions are classified as unstructured. Lack of clear decision criterion and the difficulty in identifying a finite set of alternatives and high levels of uncertainty concerning the consequences of the known alternatives at most of the decision levels, are all symptoms of this unstructuredness [25].

Semi-structured and unstructured decisions are made when problems are ill-defined (ill-structured). Srinivasan et al. notes that most real-world problems fall towards the unstructured end of this spectrum [20]. **Table 1** demonstrates the characteristics of structured and unstructured decisions.

4. Multi attribute decision-making methods

Engineering or management decisions are generally made through available data and information that are mostly vague, imprecise, and uncertain by nature [26]. The decision-making process in bridge remediation is one of these ill-structured occasions, which usually need a rigorous approach which applies explicit subject domain knowledge to ill-structured (adaptive) problems in order to reformulate them as structured problems. Multi-attribute decision-making (MADM) is an efficient tool for dealing with uncertainties.

A standard feature of multi-attribute decision-making methodology is the decision matrix with m criteria and n alternative as illustrated in **Figure 4**. In the matrix C1,...,Cm and A1,.., An indicate the criteria and alternatives respectively: each row belongs to a criterion and each column describes the performance of an alternative. The score aij describes the performance of alternative Aj against criterion Ci. It has been conventionally assumed that a higher score value means a better performance [27].

As shown in **Figure 4**, weights W1,...,Wm are assigned to the criteria. Weight Wi reflects the relative importance of criteria Ci to the decision, and is assumed to be positive. The weights of the criteria are typically defined on subjective basis. The values X1,...,Xn related to the alternatives in the decision matrix are used in the Multi-Attribute Utility Theory (MAUT) methods.

$$
\begin{array}{cc|cccc|}
 & & x_1 & \cdot & \cdot & x_n \\
 & & \mathbf{A}_1 & \cdot & \cdot & \mathbf{A}_n \\
\hline
w_1 & \mathbf{C}_1 & a_{11} & \cdot & \cdot & a_{m1} \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
w_m & \mathbf{C}_m & a_{m1} & \cdot & \cdot & a_{mn} \\
\hline
\end{array}
$$

Figure 4. The decision matrix.

Generally, higher ranking value represents a higher performance of the alternative, so the item with the highest ranking is the best action item [27].

In addition to some monetary based and elementary methods, the two main families in the multi-attribute decision-making methods are those founded on the MAUT and Outranking Methods.

4.1. Elementary methods of MADM

These elementary approaches are characterized by their simplicity and their independence to computational support. They are suitable for problems with a single decision maker, limited alternatives and criteria which can rarely occur in engineering decision-making [28]. Maximin and Maximax methods, Pros and Cons analysis, Conjunctive and Disjunctive methods and the Lexicographic method are all in this category [29].

4.1.1. Maximin and Maximax methods

The Maximin method's strategy is to avoid the worst possible performance, maximizing the minimal performing criterion. The alternative, for which the score of its weakest criterion is the highest, is preferred. For example, a weight of one is given to the criterion which is least best achieved by that choice and a weight of zero to all other criteria. The strategy with the maximum minimum score will be the optimum choice. In contrast to the Maximin method, The Maximax method selects an alternative by its best attribute rather than its worst. This method is particularly useful when the alternatives can be specialized in use based upon one attribute and decision maker has no prior requirement as to which attribute this is [30].

4.1.2. Pros and cons analysis

Pros and Cons analysis is a qualitative comparison method in which positive and negative aspect of each alternative are assessed and compared. It is easy to implement since no mathematical skill is required [29].

4.1.3. Conjunctive and disjunctive methods

The conjunctive and disjunctive methods are non-compensatory screening methods. They do not need criteria to be estimated in commensurate units. These methods require satisfactory rather than best performance in each attribute, i.e., if an action item passes the screening, it is adequate [31].

In Conjunctive method, an alternative must meet a minimal threshold for all attributes while in disjunctive method; the alternative should exceed the given threshold for at least one attribute. Any option that does not meet the rules is deleted from the further consideration [28].

4.1.4. Decision tree analysis

Decision trees provide a useful schematic representation of decision and outcome events, provided the number of courses of action, ai, and the number of possible outcomes, Oij, not large. Decision trees are most useful in simple situations where chance events are dependent on the courses of action considered, making the chance events (states of nature) synonymous with outcomes [25].

Square nodes correspond to decision events. Possible courses of action are represented by action lines which link decision events and outcome (chance) events. Circular nodes differentiate the outcome events from the decision events in order to underline that the decision-maker does not have control when chance or Nature determines an outcome [1].

The outcomes for each alternative, originates from the chance nodes and terminate in a partitioned payoff/expected value node. The expected value for each course of action is achieved by summing the expected values of each branch associated with the action [25].

A decision tree representation of a problem is shown below as an example. Three strategies (courses of action) are investigated (See **Figure 5**):

a1: replace the distressed bridge section (it would soon be unsafe)

a2: rehabilitate the bridge (repair costs will not be prohibitive)

a3: do nothing (the symptoms are more superficial than structural)

The estimated costs of replacement and rehabilitation are $6.3 M and $1.1 M respectively. If the road section is replaced, it is assumed that no further capital costs will be incurred. If the road is rehabilitated and repairs are not satisfactory, an additional $6.3 M replacement cost will result. If no action is taken and the road consequently requires major repairs or becomes totally unserviceable, respective costs of $6.3 M and $18 M will apply (Lemass [1]).

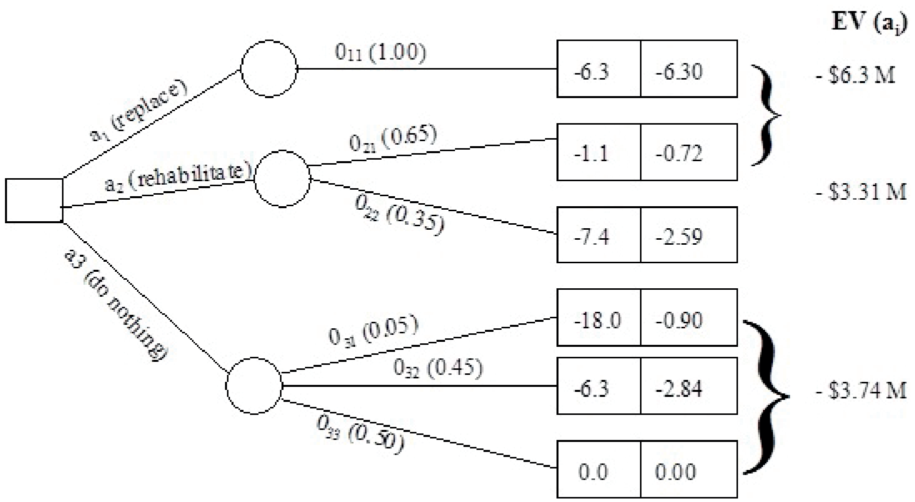

Figure 5. A decision tree for selecting the best remediation strategy of a bridge.

In this example, states of nature are the same as possible outcomes. The outcomes and associated negative payoffs (costs in millions of dollars) can be considered as follows:

Payoff		
S1 = O11:	the bridge section is successfully replaced	u11 = − $ 6.3
S2 = O22:	the repairs are satisfactory	u22 = − $ 1.1
S3 = O23:	the repairs are unsatisfactory	u23 = − $ 7.4
S4 = O34:	the bridge section fails, becoming unserviceable	u34 = − $ 18.0
S5 = O35:	the bridge section requires major repairs	u35 = − $ 6.3
S6 = O36:	the bridge section remains satisfactory	u36 = − $ 0.0

The expected value (cost) of action a2 is the lowest, based on the probability (likelihood of occurrence) assigned for each outcome, pij and this course of action can be followed [9].

4.1.5. Lexicographic method

In lexicographic analysis of problems, a chronological elimination process is continued until either a single solution is found or all the problems are solved. In this method criteria are first rank-ordered in terms of importance. The alternative with the best performance score on the most important criterion is selected. If there are ties related to this attribute, the performance of the joined option on the next most important factor will be compared until the unique alternative is chosen [31].

4.1.6. Cost-benefit analysis (CBA) and cost-effectiveness analysis (CEA)

The concept of cost–benefit analysis (CBA) originated in the United States in the 1930s where it was used to find a solution to problems of water provision. This method is used to estimate all the costs and benefits associated with a particular project which is usually defined in money terms, in order to weigh up whether a project will bring a net benefit to the public and to be able to compare the possible options for limited resources. It is one of the most comprehensive and at the same time the most difficult technique for decision-making [32].

According to Kuik et al. the application of CBA in an integrated assessment causes the following concerns [33]:

- First, CBA measures costs and benefits on the basis of subjective preferences given objective resource constraints and technological possibilities and should probably be evaluated on a case−by−case basis as an open question.
- Second, certain costs and benefits which are in the social and environmental domains might be difficult to quantify in monetary terms.

4.2. Multi attribute utility theory (MAUT)

MAUT is based upon the use of utility functions. Utility functions are employed to quantify the preference of the decision-maker by allocating a numerical index to different degrees of satisfaction as the attribute under consideration takes values between the most and least defined limits [34]. They are considered a compliant tool of representing how much an attribute (or a measure) satisfies the decision-maker objectives to transform the raw performance values of the alternatives against diverse criteria, both factual (quantitative) and judgmental (qualitative), to a general dimensionless scale [35]. They represent a means to translate attributes units into utility units. Utility functions can be specified in terms of a graph, table or mathematical expression. Mathematical expressions of utility functions include: straight-line, logarithmic, or exponential functions [34].

The utility values are estimated by normalizing the output of the simulation tests. Normalization of performance measures is conducted utilizing the minimum and maximum limits that are obtained from the simulation. Moreover, they are commonly checked against the outputs and replaced if there are values beyond the limits. The utility functions can be monotonic in a way that the least desirable scenario corresponds to the lowest utility [U(xi) =0] while the most desirable scenario matches with the highest utility [U(xi) =1.0], the interval [0,100] can also be used for this purpose [34].

4.2.1. Simple multi-attribute rating technique (SMART)

Simple Multi Attribute Rating Technique (SMART) is a method that used to determine the weights of the attributes. This method was initially developed by Edwards [50] and is based on direct numerical ratings that are aggregated additively. There are many derivates of SMART, also including non-additive methods. In a basic format of SMART, there is a rank-ordering of action items for each criterion setting the worst to zero and the best to 100 and interpolating between [27]. By filtering the performance values with associated weights for all criteria a utility value for each option is estimated [36].

SMART is independent of the action items/alternatives. The advantage of this approach is that the assessments are not relative; hence shifting the number of options will not change the final outcomes. If new alternatives are likely to be added, and the action items are compliant to a rating model, then SMART can be a better option [37].

One of the limitations of this technique is that it disregards the interrelationships between parameters. However, SMART is a valuable technique since it is uncomplicated, easy and quick which is quite important for decision makers. In SMART, changing the number of alternatives will not change the decision scores of the original alternatives and this is useful when new alternatives are added [37]. He also argued that using SMART in performance measures can be a better alternative than other methods.

4.2.2. Analytical hierarchy process (AHP)

AHP is a multi-attribute decision-making technique which belongs to the class of methods known as “additive weighting methods” [28]. The AHP was suggested by Saaty and uses an objective function to aggregate various features of a decision where the main goal is to select the decision alternative that has the maximum value of the objective function [38]. The AHP is based on four clearly defined axioms (Saaty [39]). Similar to MAU/VT and SMART, the AHP is classified as a compensatory technique, where attributes/criteria with low scores are compensated by higher scores on other attributes/criteria, but contrasting the utilitarian models, the AHP employs pair wise comparisons of criteria rather than value functions or utility where all criteria are compared and the end results accumulated into a decision-making matrix [40].

The process of AHP includes three phases: decomposition, comparative judgments, and synthesis of priority. Through the AHP process, problems are decomposed into a hierarchical structure, and both quantitative and qualitative information can be used to develop ratio scales between the decision elements at each level using pair wise comparisons. The top level of hierarchy corresponds to overall objectives and the lower levels criteria, sub-criteria, and alternatives. Users are asked to set up a comparison matrix (with comparative judgments) by comparing pairs of criteria or sub-criteria. A scale of quantities -ranging from 1 (indifference) to 9 (extreme preference) is used to identify the users priorities. Eventually, each matrix is then solved by an eigenvector technique for measuring the performance [41].

The comparisons are normally shown in a comparative matrix A, which must be transitive such that if, i > j and j > k then i > k where i, j, and k are action items; for all j > k > i and reciprocal, $a_{ij} = 1/a_{ji}$. Preferences are then calculated from the comparison matrix by normalising the matrix, to develop the priority vector, by A.W = λmax.W; where A is the comparison matrix; W is the Eigen vector and λmax is the maximal Eigen value of matrix A [42].

Through the AHP process, decision-makers' inconsistency can be calculated via consistency index (CI) to find out whether decisions break the transitivity, and to what extent. A threshold value of 0.10 is acceptable, but if it exceeds then the CI is calculated by using the consistency ratio CR = CI/RI where RI is the ratio index. CI is defined as $CI = (\lambda_{max} - n)/(n - 1)$; where λmax as above; n is the dimension [43]. **Table 2** shows the average consistencies of RI.

The advantages of the AHP method are that it demonstrates a systematic approach (through a hierarchy) and it has an objectivity and reliability for estimating weighting factors for criteria [45]. It can also provide a well-tested method which allows analysts to embrace multiple, conflicting, non-monetary attributes into their decision-making.

On the other hand, the disadvantages are that the calculation of a pair-wise comparison matrix for each attribute is quite complicated and as the number of criteria and/or alternatives increases, the complexity of the calculations increases considerably. Moreover if a new alternative is added after finishing an evaluation calculation, it is very troublesome because all the calculation processes have to be restarted again [46].

The limitations of AHP are of a more theoretical nature, and have been the subject of some debate in the technical literature. Many analysts have pointed out that, the attribute weighting questions must be answered with respect to the average performance levels of the alternatives. Others have noted the possibility for ranking reversal among remaining alternatives after one

N	1	2	3	4	5	6	7	8	9	10
R1	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Table 2. Random inconsistency index, adapted from Ishizaka [44].

is deleted from consideration. Finally, some theorists go so far as to state that as currently practiced, "the rankings of (AHP) are arbitrary." Defenders of AHP, such as Saaty himself, answered that rank reversal is not a fault because real-world decision-making shows this characteristic as well [47].

4.3. Outranking methods

The most important outranking methods assume data availability roughly similar to what required for the MAUT methods. Fundamental problems with most MAUT and MAUT-related methods are handling uncertain or fuzzy information and dealing with information stated in other than ratio or interval scale. In some conditions, instead of quantitative measures descriptive expressions are frequently faced [48]. The outranking method acts as one alternative for approaching complex choice problems with multiple criteria and multiple participants. Outranking shows the degree of domination of one alternative over another and facilitates the employment of incomplete value information and, for example, judgments on ordinal measurement scale. They provide the (partial) preference ranking of the alternatives, not a principal measure of the preference relation [48]. Here the two most famous categories of the outranking methods, the ELECTRE and the PROMETHEE methods are briefly explained.

4.3.1. The ELECTRE methods

The ELECTRE method is a part of MCDA (multi criteria decision-aid). The main aim of the ELECTRE method is to choose alternative that unites two conditions from the preference concordance on many evaluations with the competitor and preference discordance was supervised by many options of the comparison. The starting point is the data of the decision matrix assuming the sum of the weights equals to 1 [49]. As shown in Eq. (1), for an ordered pair of alternatives (Aj, Ak), the concordance index Cjk is the sum of all the weights for those attributes where the overall performance of Aj is least as high as A_k.

$$C_{jk} = \sum_{a_{ij} \geq a_{ik}} w_i \qquad j, k = 1, \ldots, n, \qquad j \neq k \tag{1}$$

The concordance index must lies between 0 and 1.

The calculation of the discordance index djk is more complex. If Aj performs better than Ak on all criteria, the discordance index will be zero. Otherwise, as per Eq. (2):

$$d_{jk} = \max \frac{a_{ik} - a_{ij}}{\max a_{ij} - \min a_{ij}} \qquad j, k = 1, \ldots, n, \qquad j \neq k \tag{2}$$

Therefore for each attribute where Ak outperforms Aj, the ratio is computed between the variance in performance between Ak and Aj and the maximum difference in score on the attribute/criterion concerned between the alternatives. The maximum of these ratios (must be between 0 and 1) is the discordance index [27].

This method determines a partial raking on the alternatives. The set of all options that outrank at least one other alternative and are themselves not outranked.

http://dx.doi.org/10.5772/intechopen.79390

4.3.2. The PROMETHEE methods

This method was introduced by Brans and Vincke [47], Brans et al. [17], and Edwards [50]. The scores of the decision table need not necessarily be normalized or transformed into a dimensionless scale. Higher score value indicates a better performance. It is also assumed that a preference function is associated to each attribute. For this aim, a preference function PFi(Aj, Ak) is defined showing the degree of the preference of option A_j over A_k for criterion C_i:

0≤PFi(Aj, Ak) ≤1 and

PFi(Aj, Ak) = 0	no indifference pr preference,
PFi(Aj, Ak) ≈ 0	weak preference,
PFi(Aj, Ak) ≈ 1	strong preference, and
PFi(Aj, Ak) = 1	strict preference.

In most realistic cases, Pi is a function of the deviation d = aij-aik, i.e., PFi(Aj, Ak) = PFi(aij-aik), where PFi is a non-decreasing function, PFi(d) = 0 for d ≤ 0 and 0 ≤ PFi(d) < 1 for d > 0. The main benefit of these preferences functions is the simplicity since there are no more than two parameters in each case.

As shown in Eq. (3), multi criteria preference index π (Aj, Ak) of Aj over Ak can then be calculated considering all the attributes:

$$\pi\left(A_{j,} A_k\right) = \sum_{i=1}^{m} w_i \; P_i \; \left(A_j, A_k\right) \tag{3}$$

The value of this index is between 0 and 1, and characterises the global intensity of preference between the couples of choices [27].

For ranking the alternatives, the following outranking flows (Eq. (4) and Eq. (5)) are classified:

Positive outranking flow:

$$\varphi^{+}\left(A_j\right) = \frac{1}{n-1} \sum_{k=1}^{n} \pi \; \left(A_j, A_k\right) \tag{4}$$

Negative outranking flow:

$$\varphi^{-}\left(A_j\right) = \frac{1}{n-1} \sum_{k=1}^{n} \pi \; \left(A_k, A_j\right) \tag{5}$$

The positive outranking describes how much each option is outranking the other items. The higher $\varphi^{+}\left(A_j\right)$, the better the alternative. The negative outranking flow shows the power of A_j its outranking character.

The negative outranking flow shows how much each alternative is outranked by the others. The smaller $\varphi^{-}\left(A_j\right)$, the better the alternative. $\varphi^{-}\left(A_j\right)$ depicts the weakness of A_j its outranked character (ibid).

4.3.3. TOPSIS methods

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) which was firstly proposed by Hwang and Yoon (1981) is one of the mostly used multi-criteria decision-making techniques [45]. The basic concept of TOPSIS is that the selected option should have the shortest distance from the positive ideal solution and the farthest distance from the negative-ideal solution in a geometrical sense. Within the process an index called "similarity index" is defined to the positive-ideal option by combining the proximity to the positive-ideal and the remoteness from the negative solution- ideal option. Then the method selects a solution with the maximum similarity to the positive-ideal solution. The default assumption is that the larger the outcome, the greater the preference for benefit attributes and the less the preference for cost attributes [51]. The idea of TOPSIS can be expressed in a series of steps:

Step 1: Identify performance data for n alternatives over m attributes. Raw measurements are normalized by converting raw measures xij into normalized measures rij as follows (please see Eq. (6)):

$$r_{ij} = \frac{x_{ij}}{\sqrt{x_{ij}{}^2}} \qquad i = 1, \ldots, m, \;\; j = 1, \ldots, n \tag{6}$$

Step 2: Estimate weighted normalized ratings as per Eq. (7):

$$\text{Weighted} \quad r_{ij} = w_j r_{ij} \tag{7}$$

w_j is the weight of the jth attribute. The basis for the weights is usually an ad hoc reflective of relative importance. If normalizing was accomplished in Step 1, scale is not an issue.

Step 3: Obtain the positive-ideal alternative (extreme performance on each criterion) A+.

Step 4: Find the negative-ideal alternative (reverse extreme performance on each criterion) A−.

Step 5: Create a distance measure for each decisive factor to both positive-ideal (Si+) and negative-ideal (Si−).

Step 6: For each option/alternative, find out a ratio Ci + equal to the distance to the negative-ideal divided by the summation of the distance to the positive-ideal and the distance to the negative-ideal (as shown in Eq. (8)):

$$C_{i^+} = \frac{S_{i^-}}{\left(S^{i^-} + S^{i^+}\right)} \tag{8}$$

Step 7: Rank order all the options by maximizing the ratio (specified) in Step 6.

4.4. Sensitivity analysis

Sensitivity analysis is the method used to find whether a particular utility or probability is essential in determining the preferred alternative. There are always some uncertainties for the weights of the criteria and the scores of the alternatives against the subjective (judgmental) criteria [52]. As a result an important question is how the final ranking or the ranking values of the alternatives is sensitive to the changes of some input parameters of the decision model [27].

4.5. Summary

This chapter covers the definition of decision support system, its ideal characteristics and its background history. Different decision analysis methods including elementary methods, multi attribute utility theory and outranking methods have also been introduced and compared.

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References

[1] Lemass B. Structured Conceptual Design: The New Frontier. Sydney: Pearson Prentice Hall; 2004

[2] Turban E, Aronson J. Decision Support Systemsand Intelligent Systems. New Delhi, India: Prentice Hall; 2001

[3] Faiz R, Edirisinghe E. Decision making for predictive maintenance in asset information management. Interdisciplinary Journal of Information, Knowledge and Management. 2009;**4**:23-36

[4] Yehia S, Abudayyeh O, Fazal I, Randolph D. A decision support system for concrete bridge deck maintenance. Advances in Engineering Software. 2007;**39**(3):202-210

[5] Zoeteman A. A life cycl costing based approach to design and maintenance of railway infrastructure. Journal on Transport and Infrastructure Research. 2001;**1**(4):391-413

[6] Burstein F, Holsapple C. Handbook on Decision Support Systems. New York: Springer-Verlag; 2008

[7] Silver M. Systems that Support Decision Makers: Description and Analysis. New York: John Wiley; 1991

[8] Keen P, Scott Morton M. Decision Support Systems: An Organisational Perspective. Reading, MA: Addison-Wesley; 1978

[9] Rashidi M, Ghodrat M, Samali B, Kendall B, Zhang C. Remedial modelling of steel bridges through application of analytical hierarchy process (AHP). Applied Sciences. 2017;**7**(2):1-20

[10] Power D. Decision Support Systems Concepts and Resources for Managers. London: Greenwood Publishing Group; 2002

[11] Bonczek R, Holsapple C, Whinston A. The evolving roles of models in decision support systems. Decision Sciences. **11**(2):337-356

[12] Rashidi M, Samali B, Sharafi P. A new model for bridge management: Part a: Condition assessment and priority ranking of bridges. Australian Journal of Civil Engineering. 2016a;**14**(1):35-45

[13] Rashidi M, Samali B, Sharafi P. A new model for bridge management: Part B: Decision support system for remediation planning. Australian Journal of Civil Engineering. 2016b; **14**(1):46-53

[14] Rashidi M, Gibson P. A methodology for bridge condition evaluation. Journal of Civil Engineering and Architecture. 2012;**6**(9)

[15] Mora M, Forgionne G, Gupta J. Decision Making Support Systems: Achievements and Challenges for the New Decade. Natural Resources Planning, Silva Fennica: Harrisburg, PA; 2003

[16] Costello T, Zalkind SS. Psychology in Administration. New Jersey: Prentice Hall; 1963

[17] Brans J, Vincke P, Mareschal B. How to select and how to rank projects: The Promethee method. European Journal of Operational Research. 1986;**24**(2):228-238

[18] Churchman C. Challenges to Reason. New York: McGraw-Hill; 1968

[19] Simon H. The New Science of Management Decisions. New Jersey: Prentice-Hall; 1977

[20] Srinivasan A, Sundaram D, Davis J. Implementing Decision Support Systems: Methods, Techniques and Tools. McGraw-Hill; 2000

[21] Ghodrat M, Rashidi M, Samali B. Life cycle assessments of incineration treatment for sharp medical waste. In: Energy Technology: Carbon Dioxide Management and Other Technologies. Switzerland: Springer; 2017

[22] Bartol K, Tein M, Matthews G, Sharma B. Management: A Pacific Rim Focus. Australia: McGraw Hill; 2007

[23] Rashidi M, Kempton S, Samali B. Analysis of bridge abutment movement through a case study. In: Mechanics of Structures and Materials: Advancements and Challenges. London: 2017

[24] Rashidi M, Lemass B. A decision support methodology for remediation planning of concrete bridges. Journal of Construction Engineering and Project Management (JCEPM). 2011;**1**(2):1-10

[25] Lemass B, Carmichael D. Front-End Project Management. Sydney: Pearson Prentice Hall; 2008

[26] Devi K, Yadav S, Kumar S. Vague sets extension of fuzzy TOPSIS method. International Journal of Computational Cognition. 2009;**7**(4)

[27] Fülöp J. Introduction to decision making methods. The Journal of the Operational Research Society. 2005;**56**(1):119-122

[28] Linkov I, Satterstorm F, Kiker G, Batchelor C, Bridges T, Ferguson E. From comparative risk assessment to multi-criteria decision analysis and adaptive managament: Recent developments and applications. Environment International. 2006;**32**(8):1072-1093

[29] Baker D, Bridges D, Hunter R, Johnson G, Krupa J, Murphy J, Sorenson K. Guidebook to Decision Making Methods. USA: Department of Energy; 2002

[30] Yoon P, Hwang C. Multiple attribute decision making: An introduction. Journal of Behavioral Decision Making. 1995

[31] Zavadskas E, Ustinovichius L, Turskis Z, Shevchenko G. Application of verbal methods to multi-attribute comparative analysis of investment risk alternatives in construction. Computer Modelling and New Technologies. 2007;**12**(4):30-37

[32] Williams B. Cost-benefit analysis. Economic & Labour Market. Review. 2008

[33] Kuik O, Navrud S, Pearce D. Pearce, Pricing the European Environment. Benefits, Estimates and Environmental Decision-Making; 1992

[34] Marzouk M. Utility theory model for equipment selection. Construction Innovation. 2006; **6**(1):21-32

[35] Rashidi M, Lemass B, Gibson P. A decision support system for concrete bridge maintenance. AIP. 2010

[36] Nemati S, Rashidi M, Samali B. Decision making on the optimised choice of pneumatic formwork textile for foam-filled structural composite panels. International Journal of GEOMATE. 2017;**13**(39):220-228

[37] Valiris G, Chytas P, Glykas M. Making decisions using the B alance scorecard and the simple multi-attribute rating technique. Performance Measurement and Metrics. 2005; **6**(3):159-171

[38] Saaty T. A scaling methods of priorities in hierarchical structures. Journal of Mathematical Psychology. 1977;**15**(3):234-281

[39] Saaty T. Response to Holder's comments on the Analyic hierarchy process. Journal of the Operational Research Society. 1991;**42**(10):918-924

[40] Bello-Dambatta A, Farmani R, Javadi AA, Evans BM. The analytical hierarchy process for contaminated land management. Advanced Engineering Informatics. **23**(4):433-441

[41] Cheng S, Chen MY, Chang HY, Chou T. Semantic-based facial expression recognition using analytical hierarchy process. Expert Systems with Applications. **3**(1):86-95

[42] Saaty T. Decision making- the analytical hierarchy and network processes (AHP/ANP). Journal of Systems Science and Systems Engineering. 2004;**13**(1):1-35

[43] Kim S, Song O. A MAUT approach for selecting a Dismantlin scenario for the thermal column in KRR-1. Annals of Nuclear Energy. 2009;**36**(2):145-150

[44] Ishizaka A. Development of an Intelligent Tutoring System for AHP (Analytical Hierarchy Process). University of Basel, ZDepartment of Business and Economics; 2004

[45] Kangas A, Kangas J, Pykalainen J. Outranking methods as tools in strategic natural Resurces planning. In: Fennica S, editor. 2001. pp. 215-227

[46] Chih Huang W, Hua Chen C. Using the ELECTRE II Method to Apply and Analyse the Differentiation Theory. The Eastern Asia Society for Transportation Studies; 2005

[47] Brans J, Vincke P. A preference ranking organisation method: (the PROMETHEE method for multiple criteria decision making). Management Science. 1985;**31**(6):647-656

[48] Kilic H. Supplier selection application based on a fuzzy multiple criteria decision making methodology. Online Academic Journal of Information Technology. 2012

[49] Elbehairy H, Hegazy T, Elbeltagi E, Souki K. Comparison of two evolutionary algorithms for optimisation of bridge deck repairs. Computer-Aided Civil and Infrastructure Engineering. 2006;**21**:561-572

[50] Edwards W. The engineering economic summer symposium series. Social Utilities. 1971;**6**: 119-129

[51] Rashidi M, Ghodrat M, Samali B, Kendall B, Zhang C. Remedial modelling of steel bridges through application of analytical hierarchy process (AHP). Applied Sciences. 2017;**7**(2)

[52] Rashidi M, Samali B, Azad A, Hatamian H. "Asset management of steel bridges," in Mechanics of Structures and Materials: Advancements and Challenges. Perth, W. A: CRC Press; 2016