An integrated sustainability decision-support framework Part II: Problem analysis

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SUMMARY

One of the main goals in decision-making for sustainable development is to identify and choose the most sustainable option among different alternatives. This process usually involves a large number of stakeholders with multiple, often conflicting objectives. Facilitating and resolving such difficult decision situations can be complex, so that a more formal and systematic approach to decision-making may be necessary. This paper proposes an integrated multiple criteria decision-support framework specifically developed to provide a systematic, step-by-step guidance to decision-makers. The framework, which is suitable for both corporate and public policy-making in the context of sustainable development, comprises three steps: problem structuring, problem analysis and problem resolution. This paper concentrates on problem analysis and resolution, where decision-makers articulate their preferences for different decision criteria. A suitable Multiple Criteria Decision Analysis (MCDA) technique, such as multi-objective optimisation, goal programming, value-based and outranking approaches, is then used to model the preferences. These techniques are discussed here in some detail, to provide guidance on the choice of the most appropriate MCDA method. Based on the outcome of preference modelling, which estimates the overall 'value' of each alternative being considered, decision-makers can then choose the 'best' or most sustainable option. Such an integrated decision-support framework is useful for providing structure to the debate, ensuring dialogue among decision-makers and showing trade-offs between conflicting objectives. In this way, it may be possible to create shared understanding about the issues, generate a sense of common purpose and, often, resolve 'difficult' decision problems.

INTRODUCTION

Decision-making in the context of sustainable development is a complex process, often involving a number of different stakeholders, decision criteria and possible alternative solutions to the decision problem. To support decision-making for sustainability, this paper proposes an integrated framework, based on multiple criteria decision analysis. As discussed in Part I (Azapagic and Perdan 2005) and shown in Figure 1, the proposed framework consists of three stages:

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1. Problem structuring;

2. Problem analysis; and

3. Problem resolution.

Problem structuring involves definition of the decision problem, identification of sustainability issues and indicators, specification of alternatives and elicitation of preferences. Problem structuring was discussed in detail in Part I.

PROBLEM ANALYSIS

As shown and Figure 1, the Problem Structuring stage is followed by Problem Analysis. This involves the following steps:

- Preference modelling;

Figure 1   Integrated decision-support framework

- Comparison and evaluation of alternatives; and
- Robustness, sensitivity and uncertainty analyses.

Preference modelling

The purpose of preference modelling is to construct a 'model' of the decision-makers' value system based on their preferences, with the aim of providing guidance in identifying the preferred solution. It involves aggregation of the elicited preferences to enable identification of the most sustainable alternative. As shown in Part I, elicitation and modelling of preferences, as well as identification and comparison of alternatives, will be influenced by, but will also influence, the choice of the MCDA technique. Preference modelling is often used as one of the main describing parameters by which different MCDA techniques are distinguished.

There are a large number of different MCDA methods and, confusingly, their categorisations, depending on the particular school of thought (e.g. American or French). However, most MCDA methods are based on the assumption that decision-makers strive to make rational choices which maximise their satisfaction, and that they do it in a structured and logical manner. In this respect, they are all based on fundamental axioms about rational human behaviour, and use mathematical logic to develop ways to rank options that are demonstrably consistent with the underlying axioms. Thus, if the axioms are accepted as true, the MCDA models provide a potentially indisputable way to rank options. In this respect, MCDA methods could be viewed as normative (rather than descriptive or prescriptive) decision models. Detailed description of these methods is outside the scope of this paper; for more detailed expositions, the interested reader may wish to consult e.g. Stewart (1992), Belton and Stewart (2002) and Guitouni and Martel (1998). Therefore, the following sections give only a brief description of the MCDA approaches, with a summary of their characteristics given in Table 1. MCDA techniques can be classified into two main groups:

- Programming methods, which comprise the optimisation (e.g. Multi-Objective Optimisation, MOO) and 'satisficing' (e.g. Goal Programming, GP) approaches, and
- Multi-attribute decision analysis (MADA), with elementary, value-based and outranking approaches.
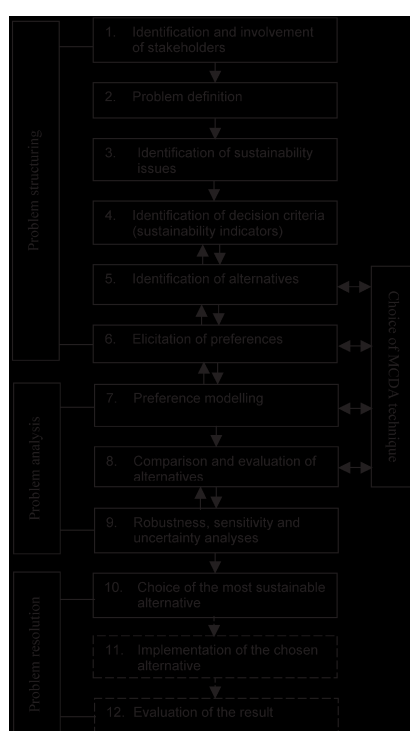
Programming methods

Optimisation approach: MOO techniques

In multiple objective optimisation (MOO) methods, the decision problem is formulated by a mathematical model, which is then simultaneously optimised (maximised or minimised) on a number of decision criteria, i.e. objectives, subject to a set of constraints. A MOO problem can be defined as follows:

$$\text{min} \qquad I(x, y) = [\,I_1\,I_2 \ldots I_K]\qquad (1)$$

$$\text{subject to:} \qquad h(x, y) = 0$$

$$g(x,y) \leq 0 \qquad (2)$$
$$x \in X \subseteq R^n$$
$$y \in Y \in Z^l$$

where I is a vector of economic, environmental and social objective functions consisting of K sustainability indicators, I_k, which in this case are being minimised (note that minimisation problems can easily be converted into maximisation models); $h(x,y) = 0$ and $g(x, y) \leq 0$ are equality and inequality constraints, and x and y are the vectors of continuous and integer (discrete) decision variables, respectively. Depending on whether the variables are linear, non-linear, continuous and/or discrete, the problem (1)–(2) can be formulated as Linear Programming (LP), Non-linear Programming (NLP), Mixed Integer Linear Programming (MILP) or Mixed Integer Non-linear Programming (MINLP). The optimisation process yields a range of Pareto optimal or non-dominant solutions in which by definition no one alternative is better on all criteria than any other alternative.

One of the main advantages of the MOO approaches is that they do not require *a priori* articulation of preferences, so that the whole set of optimum solutions can be explored in the post-optimal analysis. However, it is possible to elicit decision-makers' preferences prior to or during the optimisation process. In these cases, decision-makers specify the weights that reflect the relative importance of the objective functions. The weights are then used to aggregate the objective functions into a single function so that the above MOO problem reduces to a single objective optimisation (SOO) problem:

$$\text{min} \qquad I = \sum_{i=1}^{k} w_i I_i \qquad (3)$$

subject to the constraints in eqn. (2). For a specified set of weights of importance, SOO generates one single solution, which may be optimal but perhaps not acceptable to decision-makers. In contrast, MOO generates a range of alternatives so that decision-makers can explore the trade-offs among them. As noted in Part 1, this is particularly important in situations with multiple decision-makers, as trading-off can show explicitly what can be gained and what lost by each alternative and so help decision-makers to compromise and resolve any disputes.

MOO methods are suitable for use in corporate environments for the operational type of decisions (e.g. for design choices). Examples of the application of MOO for the operational type of decisions in the context of sustainable development (e.g. sustainable process design and optimisation) are provided by Azapagic and co-workers (1995; 1999, 2002), Kniel *et al.* (1996), Pistikopoulos *et al.* (1996), Stewart and Petrie (1996; 1999) and Alexander *et al.* (2000). In public policy-making, the MOO techniques may be helpful as a pre-screening tool to sort out the efficient from non-efficient solutions. However, they do require specialist knowledge and often sophisticated mathematical modelling skills so that their use will depend on the availability of this expertise. Furthermore, the number of alternatives obtained in MOO can still be too large for decision-makers to be able to choose the preferred one, particularly where a large number of criteria need to be considered, as is often the case in decision-making for sustainability. Therefore, to guide the choice of the 'best' solution, MOO will normally have to be followed by a post-optimal elicitation and aggregation of preferences using one of the MADA methods. In that case, MOO is used as a screening method for the elimination of non-optimal alternatives rather than as a tool for choice of the 'best' alternative. Further discussion on MOO methods in general and their application to the operational type of corporate decisions can be found in e.g. Floudas (1995).

'Satisficing' approaches

As opposed to the optimisation approaches, the emphasis in 'satisficing' is placed on achieving satisfactory rather than optimal levels of achievement on each criterion. Most methods in this category are based on identifying an ideal solution, which in

a real situation is almost always unattainable, and then defining a maximum acceptable distance from that solution. Different mathematical methods can be applied to find the feasible solution that is closest to the ideal solution, often termed a 'goal' or 'aspirational level'. Goal Programming (GP) is probably the most well-known and widely used approach in this category of MCDA methods.

GP requires decision-makers to set goals for each objective that they want to attain. A preferred solution is then defined as the one which minimises the deviations from the set goals. If the goal for the ith objective is G_i, the goal programming problem is to minimise the distance, d, from the goals:

$$\min \quad d = \sum_{i=1}^{I} \mid G_i - I_i \mid \tag{4}$$

subject to the constraints defined by eqn. (2). One of the difficulties with this method is that it may be difficult for decision-makers to define meaningful goals *a priori*, so that it may be more productive to use an interactive approach for identification of goals. In this way, an initial set of goals can be specified for each criterion, to find a starting GP solution. This solution then serves as a starting point for modifying the goals and generating the next solutions and so on, until the decision-maker is satisfied.

There are a number of modifications of the GP method defined by eqn. (4), including the use of weights to indicate the relative importance of objectives and their deviation from the specified goals. In effect, this is a variation on the objective function defined by eqn. (3). Another related method, the reference point approach, instead of goals uses reference levels of achievement which are used to explore iteratively the decision space (Belton and Stewart 2002). Whichever the method, however, sensitivity analysis should be conducted on the goals and weights to examine the change in the solution as the decision parameters change. A useful review of GP can be found in Romero (1986) and Stewart (1992).

Like MOO, GP and the related methods can also be used for screening purposes in either operational or strategic types of decisions. However, as already noted, it may be difficult for decision-makers, particularly when dealing with unfamiliar options and consequences, to identify goals or reference levels that will lead to truly 'satisfying' options. These limitations must be borne in mind if the 'satisficing' approaches are used as a tool for developing a final decision choice.

MADA techniques

As summarised in Table 1, three general types of MADA techniques are distinguished in MCDA literature:

- Elementary;
- Value- and utility-based; and
- Outranking.

Elementary methods do not require explicit evaluation of quantitative trade-offs between criteria. The value-based and outranking approaches, on the other hand, assume that decision-makers are able to articulate and 'quantify' their preferences. To facilitate this process, the value-based approaches use scores and weights to construct a 'model' of decision-maker's preference in the form of value or utility function, whereas outranking methods use outranking relations in a pairwise comparison of criteria. This is briefly explained below. More detail on these methods can be found in e.g. Hwang *et al.* (1980) and Hwang and Yoon (1981).

Elementary methods

Conjunctive and disjunctive methods: These two methods use thresholds of performance for one or more criteria to filter out the unacceptable alternatives. The conjunctive model eliminates options that fail to reach set levels of performance on each of one or more named criteria. The disjunctive model allows an alternative to 'pass' if it meets a minimum threshold level of performance on at least one of a set of named criteria. For example, in conjunctive models, to be short-listed, an alternative might be expected to reach certain minimum levels of achievement on *each* decision criteria, while in disjunctive models, it would get a 'pass' provided it exceeds the selected threshold in terms of *any* one of the key criteria. Therefore, these two methods are mainly used as 'gates' or 'filters' in generating a short list of acceptable alternatives.

Lexicographic method: In this method, decision criteria are first ranked in terms of importance and the alternative that shows best performance on the most important criterion is chosen. In effect, this method uses one single criterion as a basis for making decisions. Not surprisingly, it has not

Table 1 Summary of MCDA methods (adapted from Guitouni and Martel 1998)

	Brief description	Type of criteria	Compensation	Type of preference [and orders]	Elicitation of preferences	Preference elicitation mode	Preference modelling
			Programming methods				
Multi-objective optimisation	Involves mathematical modelling and simultaneous optimisation on a number of objectives (criteria), subject to constraints. Results in a number of Pareto optimal (or efficient) alternatives.	Cardinal	n/a	n/a [n/a]	*a priori* interactive post-optimisation	n/a Various Various	n/a Various Various
Goal programming	Requires decision-makers to set goals for each criterion that they want to attain. A preferred solution is then defined as the one which minimises the deviations from the set goals.	Cardinal	n/a	n/a [n/a]	*a priori* interactive	n/a	n/a
			MADA methods *Elementary methods*				
Lexicographic method	Decision criteria are first ranked in terms of importance and the alternative that shows best performance on the most important criterion is chosen.	Ordinal Cardinal Mixed	Non-compensatory	(P,I) [total preorders]	*a priori*	Direct rating	Cutting planes
Conjunctive method	The minimal acceptable levels for each criterion are used to screen out unacceptable alternatives: an alternative which does not meet the minimum acceptable level for all criteria is rejected.	Ordinal Cardinal Mixed	Non-compensatory	(P,I) [n/a]	*a priori*	Direct rating	Thresholds
Disjunctive method	The disjunctive model allows an alternative to 'pass' if it meets a minimum threshold level of performance on at least one of a set of named criteria.	Ordinal Cardinal Mixed	Non-compensatory	(P,I) [n/a]	*a priori*	Direct rating	Thresholds
Maximin/Maximax methods	The Maximin method scores an alternative with respect to the criterion for which its shows the worst performance. The scoring process is reversed in the Maximax model, so that the alternatives are scored with respect to the criterion for which they exhibit be best performance.	Ordinal Cardinal	Non-compensatory	(P,I) [total preorders]	*a priori*	Direct rating	Max and min operators

Table 1 *Continued*

			Value function methods				
Weighted sum	The global performance of an alternative is computed as the weighted sum of its evaluations for each criterion. The global performance is used to make a choice among all the alternatives.	Cardinal	Total compensation	(P,I) [total preorders]	a priori	Direct rating	Algebraic sum
TOPSIS (Technique for Order by Similarity to Ideal Solution)	The chosen alternative should have the profile which is the nearest (distance) to the ideal solution and farthest from the negative ideal solution. The ideal solution is formed as a composite of the best performance values exhibited by any alternative for each attribute.	Cardinal	Total compensation	(P,I) [total preorders]	a priori	Direct rating	Euclidian distances
MAVT (Multi-Attribute Value Theory)	Involves determination of partial value functions and establishing weights for each criterion to calculate a global value function, V. Additive and multiplicative models are used to obtain V.	Cardinal	Partial compensation	(P,I) [total preorders]	a priori	Trade-offs	Value aggregation (additive or multiplicative)
MAUT (Multi-Attribute Utility Theory)	Involves determination of partial utility functions to calculate a global utility function U. Additive and multiplicative models are used to obtain U.	Cardinal	Partial compensation	(P,I) [total preorders]	a priori	Trade-offs and lotteries	Utility aggregation (additive or multiplicative)
AHP (Analytic Hierarchy Process)	Measures relative importance of criteria and preferences for alternatives through pairwise comparison matrices which are recombined into an overall rating of alternatives by using eigenvalue method.	Cardinal	Partial compensation	(P,I) [total preorders]	a priori	Pairwise comparison	Eigenvector method
SMART (Simple Multi-Attribute Rating Technique)	Simple way to implement the MAUT by using the weighted linear averages, which give close approximations to utility functions. The weights are defined using ratio estimation.	Cardinal	Partial compensation	(P,I) [total preorders]	a priori	Trade-offs and direct rating	Value aggregation (additive)
UTA (Utility Theory Additive)	Estimates the value functions on each criterion using ordinal regression. The global value function is obtained using the additive model.	Ordinal	Partial compensation	(P,I) [total preorders]	a priori	Trade-offs	Value aggregation (additive)

Table 1 *Continued*

EVAMIX	Two dominance indices are calculated: one for ordinal evaluations and the other one for cardinal evaluations. The combination of these two indices leads to a measure of the dominance between each pair of alternatives.	Ordinal Cardinal Mixed	Partial compensation	(P,I) [total preorders]	*a priori*	Direct rating	Algebraic sum
Outranking methods							
ELECTRE family:	All ELECTRE methods use the concept of outranking relationships.	Ordinal Cardinal Mixed	Partial compensation	(S,R) [partial orders]	*a priori*	Pairwise comparison	Graph theory Disjunctive and conjunctive
I	An alternative is eliminated if it is dominated by other alternatives to a specific degree.						
II	Uses two outranking relations (strong and weak).						
III	The outranking is expressed through a credibility index.						
IV	Similar to ELECTRE III but does not use weights.						
TRI	Similar to ELECTRE III but uses conjunctive and disjunctive techniques.						
PROMETHEE I & II	Based on the same principles as ELECTRE. It provides a partial order of the alternatives using entering and leaving flows.	Ordinal Cardinal Mixed	Partial compensation	(P,I,R) [partial orders]	*a priori*	Pairwise comparison	Leaving and entering flows
MELCHIOR	MELCHIOR is an extension of ELECTRE IV	Ordinal	Partial compensation	(S,R) [partial orders]	*a priori*	Pairwise comparison	Graph theory (distillation)
ORESTE	This procedure needs only ordinal evaluations of the alternatives and the ranking of the criteria in terms of importance.	Ordinal	Partial compensation	(P,I,R) [partial orders]	*a priori*	Pairwise comparison	Graph theory
REGIME	A pairwise comparison matrix is built using +1 if there is dominance, 0 if the two alternatives are equivalent and ±1 for the negative-dominance. The aggregation of these weighed scores provides a total preorder of the alternatives.	Ordinal	Partial compensation	(S,R) [partial orders]	*a priori*	Pairwise comparison	Graph theory

contributed much to the practice of public sector decision-making (Dogson *et al.* 2001).

Maxmin and maximax methods: The approach in the Maximin method is to score an alternative with respect to the criterion for which its shows the worst performance. The scoring process is reversed in the Maximax model, so that the alternatives are scored with respect to the criterion for which they exhibit the best performance.

Value- and utility-based methods

The intention in these approaches is to construct a means of associating a real number with each alternative and to produce a preference order for the alternatives, based on decision-makers' value judgements (Belton and Stewart 2002). As listed in Table 1, these approaches include a number of methods, three of which have been used most extensively in various decision-making contexts and are briefly discussed below:

- Multi-attribute value theory (MAVT);
- Multi-attribute utility theory (MAUT); and
- Analytic hierarchy process (AHP).

Multi-Attribute Value Theory (MAVT): This method can be used in decision-making with certain outcomes, i.e. where decision-makers are certain about the outcomes of alternatives being considered. Typically, it involves the following three steps:

1. Intra-criteria comparison or assignment of value scores.

2. Inter-criteria comparison, or assignment of weights to decision criteria.

3. Aggregation of scores and weights to guide decision-makers in choosing the preferred alternative.

1. Intra-criteria comparison or assignment of value scores

The value score $v_k(a_n)$ reflecting the performance of alternative a_n with respect to a decision criterion (in this context, a sustainability indicator) I_k is usually represented in a performance matrix:

Decision criteria (sustainability indicators)

	I_1	I_2	...	I_K
a_1	$v_1(a_1)$	$v_2(a_1)$	...	$v_K(a_1)$
a_2	$v_1(a_2)$	$v_2(a_2)$	...	$v_K(a_2)$
Alternatives ...	...	...	...	...
a_N	$v_1(a_N)$	$v_2(a_N)$	...	$v_K(a_N)$

Scores are represented on a preference scale which shows relative strength of preferences. Scales can be either relative or fixed. The former are constructed using the available alternatives as anchors: the alternatives that perform best and worst on a particular criterion are assigned a score of 100 and 0, respectively. The performance of other alternatives is then scored relative to this scale for each criterion. Fixed scales are defined independently of the available alternatives: for example, 100 may be defined as the 'maximum feasible' and 0 as the 'minimum acceptable'. These are both interval scales, so 0 does not mean no preference or no benefit, any more than 0°C means no temperature. In some cases, ratio scales are also used. In this case the zero point is not arbitrary; it represents e.g. zero cost or no benefit.

2. Inter-criteria comparison, or assignment of weights to decision criteria

Inter-criteria comparison is related to determining the relative importance of different criteria. Here, decision-makers are asked to assign numerical weight to each criterion to define its importance relative to the other criteria considered in a particular decision-making situation. There are different ways to elicit weights, but most proponents of MCDA use 'swing weights' (von Winterfeldt and Edwards 1986), where the 'swing' is that from the worst (e.g. 0) to the best value (e.g. 100) on each criterion. Decision-makers are first asked to rank-order the criteria from the most to the least important: the criterion for which the swing from the worst to the best value gives the greatest increase in overall value is deemed the most important; the process is repeated until all the criteria have been ranked. If the number of criteria is small, comparisons can be made by considering all criteria simultaneously. However, if there are many criteria, then a pairwise comparison may be more appropriate: two criteria are compared at a time for their preference swings, always retaining the

one with the bigger swing to be compared to a new criterion.

The next step is to assign the numerical weights to the criteria to show how much the 'swing' on each criterion matters to decision-makers. For example, decision-makers could be asked, for each criterion, to assess the increase in the overall value resulting from an increase from a score of 0 to 100 on the selected criterion as a percentage of the increase in overall value resulting in an increase from a score of 0 to 100 on the most highly ranked criterion. If for instance, decision-makers perceive the increase in the overall value on the second-ranked criterion is worth 50% of the first-ranked criterion, then the value of weight assigned to the

second criterion is 0.5 of the weight assigned to the first criterion (usually taken to be 1). The weights can also be normalised to sum 1 or 100.

In decision problems with a large number of criteria, it is useful to define relative and cumulative weights and represent these on the value trees. Relative weights are assessed within the criteria which share the same 'parent', while the cumulative weight of a criterion is the product of its relative weight compared to the other criteria in the same family and the relative weight of its parent, and so on until the top of the tree is reached. For example, in Figure 2, the cumulative weight of the criterion 'rate of loss of species' is equal to 0.06 and is obtained by multiplying its relative weight of 0.2
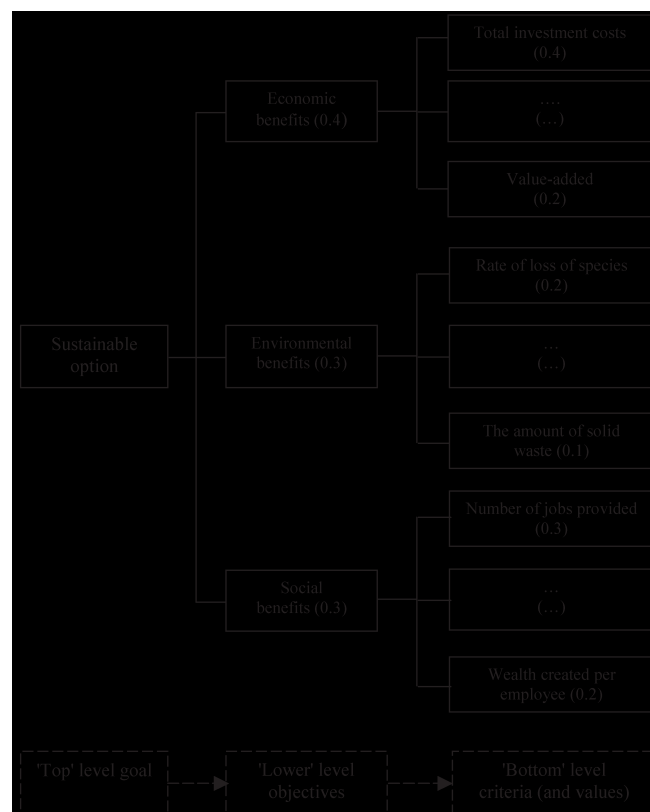

Figure 2   An example of a 'value tree' and (hypothetical) preferences for different sustainability objectives and criteria

by the relative weight of 0.3 of its parent 'environmental benefits'.

As the assessment and interpretation of the importance weights is likely to affect the choice of the preferred alternative, it is important to ensure that interpretation of weights is consistent with the model being used and understood by all decision-makers. It is also important to bear in mind that in deriving the weights there is a natural implicit trade-off interpretation, so that the weights can only be assessed and interpreted within the contexts of the ranges of available alternatives.

3. Aggregation of scores and weights

After preferences, i.e. the scores and weights have been elicited, the aggregation step is carried out to generate an overall value function. Aggregation can be applied either across all the criteria in a single operation or may be applied hierarchically by aggregating at each level of the value tree across the criteria that share the same 'parent' criterion (Belton and Stewart 2002). In the latter case, the aggregation is repeated, moving from one hierarchical level to the next, until the overall aggregation is achieved. Taking the example of the value tree shown in Figure 1, the former approach would aggregate directly all preferences expressed for the 'bottom level' criteria, leading to a single value function related to the 'top level' goal defined as 'choosing the most sustainable option'. In the latter approach, preferences for the 'bottom level' criteria would first be aggregated to the next higher level, e.g. investment costs and value added would be aggregated to obtain total preference score for 'economic benefits'. This process would continue until sustainability preferences are obtained by aggregation of economic, environmental and social benefits.

The form most widely used for preference aggregation in MAVT is the additive model:

$$V(a_n) = \sum_{k=1}^{K} w_k v_k(a_n) \tag{5}$$

A bit more complicated, multiplicative model is also sometimes used:

$$V(a_n) = \prod_{k=1}^{K} \{v_k(a_n)\}^{w_k} \tag{6}$$

where:

$V(a_n)$ – overall value of alternative a_n

$v_k(a_n)$ – value score reflecting the performance of alternative a_n on criterion I_k

w_k – weight assigned to reflect the importance of criterion I_k.

If the values related to the individual criteria have been assessed on a 0 to 100 scale and the weights are normalised to sum 1, then the overall values will lie on a 0 to 100 scale. In both models, the higher the $V(a_n)$, the more desirable the alternative. Also, both models require that the criteria should be preferentially independent. This means that the judged strength of preference for an option on one criterion should be independent of its judged strength of preference on another.

There is evidence that decision-makers, when confronted with difficult multiple criteria choices, almost instinctively turn to some form of simple comparison and aggregation of criteria (Stewart 1992; Belton and Stewart 2002). It may therefore be practicable and justifiable to use easily understood additive scoring instead of more sophisticated methods, providing that the definition of criteria and the scoring methods used are fully understood and agreed on by decision-makers.

Multiattribute Utility Theory (MAUT): While MAVT is not able to take uncertainty into account, MAUT allows the comparison of alternatives with uncertain outcomes through the computation of 'expected utility'. Calculating the expected utility involves weighting utilities by the probabilities for all anticipated consequences of each alternative, then summing those products according to the following formula:

$$U(a_n) = \sum_{j=1}^{J} p_j u_j(a_n) \tag{7}$$

where:

$U(a_n)$ – overall utility (preference score) of alternative a_n;

u_j – utility of alternative a_n if its choice leads to consequence j;

p_j – decision-maker's best judgement of the probability that consequence j will occur.

The alternative with the highest expected utility should be the preferred option.

MAUT is one of the most widely used MADA techniques, particularly for public policy-making (Dogson *et al.* 2001). Some of the most

important and far-reaching applications recently have concerned decisions about the reprocessing or storage of nuclear waste. However, calculations of utility function can be quite complex (see Keeney and Raiffa 1976). Nevertheless, in many applications it may not be necessary to use the more complicated MAUT models as simple additive functions similar to those defined by eqn. (5), examined carefully by sensitivity analysis, may be adequate in most cases (Belton and Stewart 2002).

Analytic Hierarchy Process (AHP): MAVT and AHP have many similarities (Belton and Stewart 2002). Both methods are based on evaluating the alternatives in terms of an additive model defined by eqn. (5). Therefore, AHP could be viewed as a value-based approach, although some AHP proponents consider AHP as a completely different method. The major difference between MAVT and AHP is that the latter uses pairwise comparisons in comparing the decision criteria and alternatives to elicit weights and scores, respectively (see Saaty 1980). Thus, for example, in assessing decision criteria weights, the decision-maker is asked a series of questions, each of which tries to find how important one particular criterion is relative to another in the context of that particular decision problem. The same process is repeated for the comparison of alternatives, whereby the score is calculated for each alternative by evaluating their performance on each criterion. A 9-point ratio (rather than interval) scale is used for all judgements, so that ratio 1 means that the two compared criteria are equally important, 3 that one criterion is moderately more important and so on to the ratio of 9, which means that one criterion is most important.

The strengths and weaknesses of the AHP have been the subject of substantial debate among specialists in MCDA. It is clear that users generally find the pairwise comparison form of data input straightforward and convenient. This feature is also exploited in the outranking methods (see next section). On the other hand, serious doubts have been raised about the theoretical foundations of the AHP and about some of its properties. In particular, the 'rank reversal' phenomenon has caused concern. This is the possibility that, simply by adding another option to the list of options being evaluated, the ranking of the other options, not related in any way to the new one, can be reversed. This is seen by many as inconsistent with rational

evaluation of options and thus questions the underlying theoretical basis of the AHP. In response to this criticism, Saaty (1990) proposed a new approach, a so-called 'absolute measurement mode'. In this approach, a number of 'absolute' levels of performance on each criterion are defined which are then pairwise-compared to generate numerical scores for each level of performance.

Outranking methods

These approaches, developed in France (see e.g. Roy 1985), differ from the value- and utility-based approaches in that there is no underlying aggregate value or utility function (Belton and Stewart 2002). Like the AHP, they also use pairwise comparison between every pair of alternatives being considered, but the aim is to eliminate alternatives that are dominated. Thus, the output of decision analysis is not a value for each alternative, but an outranking relation on the set of alternatives. In general, alternative a_1 outranks a_2 if there is 'sufficient' evidence to justify a conclusion that a_1 is at least as good as a_2 for all criteria (Belton and Stewart 2002).

As shown in Table 1, there are a number of different outranking methods, including the family ELECTRE, PROMETHEE and MELCHIOR. Typically, they all involve two phases: first, a way of determining whether one alternative outranks another is specified and second, it is necessary to determine how all the pairwise outranking assessments can be combined to suggest an overall preference ranking among the options. Two outranking principles are used (Guitouni and Martel 1998; Belton and Stewart 2002):

- Concordance principle: a_1 outranks a_2 if it is as good as or better than a_2 according to a sufficiently large weight of criteria; and
- Discordance principle: if a_2 is strongly preferred to a_1 then this is considered to be evidence against a_1 outranking a_2.

Similar to the conjunctive and disjunctive elementary methods mentioned earlier, these approaches also use thresholds beyond which bad performance on one criterion cannot be compensated for by good performance on another criterion.

Outranking methods have been promoted for their non-compensatory approach to decision-making and for the ease with which uncertainties can be incorporated explicitly into the evaluation

of differences between alternatives (Sepälä *et al.* 2002). However, the main concern voiced about the outranking approach is that it lacks theoretical backing (Guitouni and Martel 1998), particularly in terms of some rather arbitrary definitions of what precisely constitutes outranking and the way the threshold parameters are set and later manipulated by the decision-maker (Dogson *et al.* 2001).

Fuzzy and rough sets

Although these are not MCDA techniques, but tools that can be applied in any of the above methods, for completeness, they are briefly outlined here.

Fuzzy sets theory has been developed to help decision-makers deal with fuzzy or imprecise information. It uses a so-called 'membership function' to indicate the extent to which a statement is true, rather than expressing the absolute truth. For example, traditional mathematics used in MCDA methods is based on 'crisp' logic in which a statement that one alternative is preferred over another is either true or false (Belton and Stewart 2002). Fuzzy sets theory, on the other hand, indicates the extent to which one alternative is preferred to another, or the 'truth value' of that statement. This theory is appealing in the context of MCDA and has found wide application within the MCDA techniques because human preferences are more often than not expressed in a fuzzy way. For example, ordinal preference statements and outranking relationships are often found to be expressed in a fuzzy way.

The theory of rough sets deals with imperfection of information. For example, in the absence of complete information it may not be possible to distinguish between two alternatives; however, if more information is provided, they may be found to be quite different.

Further detail on these theories can be found in Greco *et al.* (1999).

Main differences between MCDA techniques

Prior to returning to the description of the decision-support framework, it may be useful to summarise the differences between the MCDA techniques that are important for decision-making in the context of sustainable development. In addition to elicitation of preferences and the models for their preferences which have been discussed above, the MCDA methods also differ with respect to:

- Type of decision criteria;
- Type and number of alternatives;
- Approach to compensation among decision criteria; and
- Preference ordering.

These factors will influence the decision-making process and its outcome, so that the main challenge is to choose the MCDA method that is most appropriate for a particular decision-making situation. Let us therefore briefly examine these differences, which are also summarised in Table 1.

Decision criteria

In multiple criteria analysis the following four types of criteria are used:

- **Cardinal or measurable criterion:** enables preferential comparison of intervals of the evaluation scale. The following sub-types can be distinguished:
  - True-criterion (without any threshold);
  - Semi-criterion (with indifference threshold); and
  - Pseudo-criterion (with indifference and preference thresholds).
- **Ordinal or qualitative criterion:** defines only an order of alternatives, thus the evaluation scale is discrete.
- **Probabilistic criterion:** used to describe the level of uncertainty in the outcome of an alternative.
- **Fuzzy criterion:** describes imprecise and ambiguous information by using the membership function to indicate to what extent a certain statement is true.

Sustainability indicators can be represented in any of the above forms. For example, 'global warming' is a measurable criterion associated with uncertainty. Research in climate change shows that there may be different thresholds above which the effects of global warming will lead to different events such as floods, droughts, etc. In this respect, it is possible to define global warming as either a semi- or pseudo-criterion. Furthermore, 'job satisfaction' can be both measurable and a qualitative criterion but it can also be expressed as a fuzzy criterion,

indicating a degree of job satisfaction. Table 1 shows the type of criteria used by different MCDA techniques. All programming and most value-based approaches use cardinal information, while the elementary and outranking methods can deal with ordinal, cardinal or mixed type of information.

Alternatives

MCDM techniques are often distinguished according to the problems they address with respect to the number and type of alternatives decision-makers have to choose from so that they are classified as:

- Continuous problems with an infinite number of alternatives, or
- Discrete problems with a finite set of alternative options.

In this respect, problems addressed by programming methods are considered to be continuous, while those analysed by MADA are said to be discrete (Sepälä *et al.* 2002). However, this distinction could be misleading and merits an explanation. It is true that before multi-objective optimisation (MOO) or goal programming (GP) is performed, there are an infinite number of possible alternatives. However, the main aim of both MOO and GP is to generate a set of (often still large but) finite and discrete alternatives. As already noted, in MOO, they are known as Pareto optimal or efficient solutions, while in GP they are described as solutions that best satisfy some pre-specified goal. In both cases, the decision-maker is then faced with the problem of identifying the preferred out of a number of solutions so that the problem in effect is that of choosing from a set of discrete rather than continuous alternatives. Therefore, as discussed in above, programming techniques can be used as a screening tool to reduce an infinite number of alternatives to a smaller, discrete set of options. However, the number of solutions, particularly those obtained in MOO, will probably still be quite large, so that the choice of the preferred alternative will have to be aided further by an MADA technique.

Compensation

With respect to assessment of the performance in one criterion relative to another, the MCDA methods can either be (Colson and De Bruyn 1989):

- Compensatory, whereby a bad performance on one criterion can be compensated by a good performance on another;
- Non-compensatory: no compensation is accepted between the different criteria whereby decision-makers consider that all criteria are important enough to refuse any kind of compensation or trade-off;
- Partially compensatory: in this case, some kind of compensation is accepted between the different criteria; the major problem here is to evaluate the degree of compensation for each criterion.

As shown in Table 1, most MCDA methods are partially compensatory (Guitouni and Martel 1998), despite indications that most decision-makers use either non-compensatory or compensatory strategies in articulating their preferences (Kottemann and Davis 1991). The choice of the MCDA technique with respect to compensation is particularly important in the context of sustainable development, because the question of compensation raises an important ethical question: for example, can good economic performance compensate for poor environmental performance, and if so, what degree of compensation is acceptable? Answering this question is also part of the decision-making process, particularly in multiple decision-maker situations and it should be explored thoroughly by the stakeholders before an MCDA method is chosen. Ongoing research is addressing this problem (e.g. Basson 2002).

Preference ordering

As most MCDA methods use decision-makers' preferences to identify the 'best' alternative, the choice of appropriate model for preference ordering is fundamental for decision-making. This is particularly important in the context of sustainability decision-making because of the multiplicity of decision criteria and interest groups, so that the choice of the MCDA technique must take into account how strongly decision-makers feel about different criteria and alternatives and what is the most meaningful approach to ranking the alternatives. With respect to the former, most MCDA methods use the following five basic binary relationships to order preferences (Roy 1985):

- Strict preference $(a_1 \text{ P } a_2)$: decision-makers strongly prefer alternative a_1 over alternative a_2 for a particular decision criterion;
- Indifference $(a_1 \text{ I } a_2)$: alternative a_1 is as preferable as alternative a_2;
- Weak preference $(a_1 \text{ Q } a_2)$: alternative a_1 is at least as preferable as alternative a_2;
- Incomparability of preferences $(a_1 \text{ R } a_2)$: it is not possible for decision-makers to compare alternatives a_1 and a_2; and
- Outranking relationship $(a_1 \text{ S } a_2)$: a_1 outranks a_2.

According to these relationships, the alternatives can be ranked in (Janssen 1992; Sepälä *et al.* 2002):

- Complete orders $(a_1 \text{ P } a_2 \text{ P } a_3 \text{ P} \ldots a_n)$: no two alternatives are regarded as equal;
- Complete pre-orders $(a_1 \text{ P } a_2 \text{ I } a_3 \text{ P} \ldots a_n)$: some alternatives are considered equal; and
- Partial orders $(a_1 \text{ P } a_2 \text{ R } a_3 \ldots \text{P} \ldots a_n)$, some alternatives may not be ranked relative to the others.

The ranking of alternatives where decision-makers do not indicate the degree to which one alternative is preferred to another is known as ordinal ordering of preferences. Cardinal ordering, in addition to ordering the alternative, also indicates a level of preference for each alternative; e.g. a_1 is two times more preferable than a_2.

Decision-support software

As shown in Table 2, a number of decision-support software packages are available. Most support single decision-maker situations with only a few supporting group or multiple decision-maker systems (e.g. PRIME, Team Expert Choice, Web-HIPRE and WINPRE). A new package, currently being developed at the University of Sydney (see Table 2 for details), is specifically tailored to support decision-making in the context of sustainable development. In the absence of commercial MCDA software, it is also possible to use simple spreadsheet packages, such as Excel. Excel's Solver will also handle smaller optimisation problems.

Choice of MCDA method

The choice of the 'right' MCDA method in any decision context will depend on many factors, but the following principles should be used as a guide (Dogson *et al.* 2001; Stewart 1992):

- Ease of use by non-experts;
- Transparency of the logic of the method to decision-makers;
- Freedom from ambiguity regarding interpretation of inputs required from decision-makers;
- Internal consistency and logical soundness;
- Data requirements not inconsistent with the importance of the issue being considered;
- Realistic time and human resource requirements for the analysis;
- Ability to provide an audit trail (i.e. a structured written record that enables an investigator to trace the path of past actions or decisions); and
- Software availability, where needed.

In addition to these general considerations, in choosing an MCDA method for decision-making in the context of sustainable development, it will also be important to consider suitability of the methods with respect to the factors discussed in the preceding sections. To summarise, the following are the particular characteristics of different MCDA methods that may be relevant for sustainability decision-making:

- **Multi-objective optimisation** does not require elicitation of preferences and therefore implicitly considers all decision criteria to be of equal importance. It is suitable for screening purposes to separate out non-efficient from efficient solutions, where the choice among the latter can then be facilitated by any of the MADA methods. In practice, this method is used in corporate decision-making for operational types of decision. One of the advantages of MOO is that it provides decision-makers with a range of Pareto efficient alternatives so that the trade-offs between them can be fully explored.
- **Goal programming and reference point methods** are suitable for situations in which decision-makers find it difficult to express trade-offs or importance weights, but are able to identify the aspirations or goals for the outcomes of alternatives that they would find satisfying. Like MOO, these methods are also more suited for use in early stages of problem analysis, to generate a short-list of alternatives for more detailed evaluation in later stages of the analysis. In an interactive mode, goal programming can help decision-makers to understand better the structure of the problem and to narrow the search

Table 2   Selection of commercially available decision-support software (adapted from Belton and Stewart 2002)

Package	Types of problems and decisions supported	Methodology	Web address
GAMS	Single and multi-objective optimisation	LP, NLP, MILP, MINLP	http://www.gams.com
WWW-NIMBUS	Multi-objective programming	Interactive and reference point methods	http://nimbus.mit.jyu.fi
XPRESS-MP	Single and multi-objective optimisation, goal programming	LP, MILP, Goal programming	http://www.dash.co.uk
Criterium Decision Plus	Discrete	Value function model based on trade-off analysis	http://www.infoharvest. com
DataScope	Discrete and continuous	Multi-attribute value functions	http://www.cygron.com
Decision Explorer	Problem structuring for general decision contexts	Qualitative data analysis, linking concepts through cognitive maps	http://www.banxia.com
Decision Lab 2000	Discrete	PROMETHEE/GAIA	http://visualdecision.com
DEFINITE	Discrete	Multi-attribute value functions; cost-benefit analysis; outranking	marjan.van.herwijnen@ ivm.vu.nl
ELECTRE III, IV, IS & TRI	Discrete	ELECTRE outranking methods	http://www.lamsade. dauphine.fr
High Priority	Discrete	Multi-attribute value functions	http://www.kysalis.co.uk
HIVIEW	Discrete	Multi-attribute value functions	http://www.enterprise-lse.co.uk
Logical Decisions	Discrete	Multi-attribute value functions and AHP	http://www.logicaldecisions.com
MACBETH	Discrete	Multi-attribute value functions using pairwise comparisons	http://www.umh.ac.be/ vansnick/macbeth.html
MCDA DSS	Discrete	Multi-attribute value functions; outranking	Petrie@chem.eng.usyd.edu.au
PRIME	Discrete	Multi-attribute value functions with imprecise preference information	http://www.hipre.hut.fi/ donwloadables/
Team Expert Choice	Discrete	AHP	http://www.expertchoice. com
V.I.S.A	Discrete	Multi-attribute value functions	http://www.SIMUL8.com/ visa.htm
Web-HIPRE	Discrete	Multi-attribute value functions and AHP	http://www.hipre.hut.fi
WINPRE	Discrete	Interactive multi-attribute value functions with imprecise preference information	http://www.hipre.hut.fi/ downloadables/

for the best solution quite considerably (Stewart 1992).

- **Elementary methods** are non-compensatory and for this reason they may be suited for decision-making where compensation is not acceptable, for example, where a good performance on an environmental criterion cannot compensate for a bad performance with respect to ethical considerations. Furthermore, they do not require explicit evaluation of quantitative trade-offs between criteria which some decision-makers find easier rather than quantitative evaluations. On the other hand, some of the methods (e.g. conjunctive and disjunctive methods) require setting of performance thresholds, which may be difficult for some of the sustainability criteria, such as identifying an 'acceptable' level of ethical performance.

- **Value- and utility-based approaches** are based on either total or partial compensation. They use explicit statements of acceptable trade-offs between different criteria and in this way facilitate construction of preferences. This may help each decision-maker to further understand their own but also the values of the other stakeholders participating in the decision-making process. These methods also provide a basis for decision-makers to justify the rationale for their final choice, which may be particularly important in public policy-making. Because of its ability to deal with uncertainty, MAUT in particular may be suitable for decision-making in the context of sustainable development, which often involves uncertain conditions and facts. The AHP method can be useful in cases where decision-makers are not comfortable with numerical scores but prefer qualitative or semantic scales (e.g. moderately important, highly important). However, the AHP uses the ratio scale, which implies the existence of a zero as the natural reference point and that the criteria can be expressed on natural ratio scales, such as mass, distance, etc. This may pose difficulties, as many sustainability indicators do not have natural ratio scales (e.g. some social and ethical considerations) and it is difficult to find clear reference levels.

- **Outranking approaches** use pairwise comparisons to assess preferences, indifferences and incomparabilities between alternatives. By recognising the fact that preferences and values

are often not pre-existing but are formed within a particular decision-making context, as is the case in multiple decision-maker situations, they help decision-makers to construct their preferences. This may be particularly helpful in 'difficult' decision-making situations as it can promote discussion and understanding between the groups and so act as a catalyst in reaching consensus. These methods are more useful for a smaller number of alternatives (less than 15–20). They can assist in understanding and visualising choices and in generating tentative partial orderings of alternatives, which may provide sufficient information for decision-makers to make the final choice (Stewart 1992) so that the more complex approaches to decision-making can be avoided.

Therefore, based on this brief summary and the information provided in Table 1, it is obvious that the choice of the 'right' MCDA method in sustainability decision-making is not an easy task because none of the methods is ideal, so that sometimes a combination of approaches may be necessary. Nevertheless, MAVT, MAUT and outranking approaches appear to be most widely used in strategic decision situations, while MOO and GP have found wider application in operational types of decision. Further guidance on the choice of MCDA techniques can be found in Guitouni and Martel (1998). In practice, probably the most influencing factor in choosing a particular MCDA method is the specialism of decision analysts and their experience in dealing with similar problems. However, while some methods naturally lend themselves for particular types of problem, perhaps the MCDA technique itself is not that important; what is important is that it provides a structure and a guide to decision-makers to explore their priorities in a meaningful way and choose an alternative that satisfies their needs.

Comparison and evaluation of alternatives

The outcome of preference modelling is the overall 'value' for each alternative being considered, which should enable decision-makers to choose the preferred option. Sometimes MCDA can return surprising results so that it may be helpful to decision-makers to test the aggregation of

information and overall evaluation against their intuitive judgements. For example, alternatives with similar overall values can have quite different profiles, so it is important to consider their strengths and weaknesses, advantages and disadvantages. An advantage is a high score on a heavily weighted criterion; a disadvantage is a low score on an important criterion. Disadvantages are important because they reduce the overall preference, whereas low scores on unimportant criteria do not.

Evaluation of alternatives may cause decision-makers to question their intuition and possibly to revise their opinions, or to revisit the model and question whether it included all of the important criteria. The aim of this analysis should be to stimulate further learning about the decision problem and ensure that subsequent decisions are taken with full awareness of possible consequences. Sensitivity and uncertainty analyses should help further in this respect.

Sensitivity, robustness and uncertainty analyses

The aim of sensitivity and robustness analysis is to investigate whether preliminary conclusions are robust and to identify to what extent changes in the input variables, assumptions and model structures would change the conclusions of the decision analysis. For these purposes, changes are made to investigate the significance of missing information and effect of decision-makers' uncertainty about their preferences. Sensitivity analysis also looks at the advantages and disadvantages of selected options and compares pairs of options. It is possible that during this process new alternatives will be identified that might be better than those originally considered. These steps are repeated until a 'requisite', i.e. 'good enough' model to resolve the problem is obtained.

Sensitivity analysis to examine how the ranking of options might change under different scoring or weighting systems can show that two or three options always come out best. If the differences between these best options under different weighting systems are small, then accepting a second-best option can be shown to be associated with little loss of overall benefit (Dogson *et al.* 2001). The reason this is usually not apparent in a debate between stakeholder groups outside a formal decision-making process is that they focus on their differences, and ignore the many criteria on which they agree. Therefore, sensitivity analysis can play a potentially useful role in helping to resolve disagreements between different stakeholder groups.

Uncertainty analysis helps to identify which uncertainties make the largest contribution to the overall uncertainty in the final outcome of the decision-making process. In this way it can assist in identifying 'hot spots' that should be targeted to reduce the uncertainty and improve the robustness of the conclusions. There are different sources of uncertainty in decision-making, but for decision-making in the context of sustainable development two types are particularly important: model and parameter uncertainties (Basson and Petrie 2001). The former refer to the assumptions made and choice of particular preference models (e.g. choice of system boundaries, sustainability criteria and indicators, scoring and weighting, evaluation of alternatives, consequences of a particular choice, etc.), and the latter to the lack of knowledge about the parameters (e.g. empirical data on environmental impacts, design variables, etc.) used to support decision-making.

Different methods can be used to deal with uncertainty. For example, the Monte Carlo method can be used to analyse uncertainty by producing distributions of value scores of alternatives (Sepälä *et al.* 2002). Scenario planning is another method for accounting for uncertainty by building a number (usually two or three) of scenarios relevant for the decision problem. Rather than trying to explicitly model the likelihood of different scenarios happening, the emphasis here is on defining good strategies which are robust over a range of possible futures. As discussed above, MAUT provides another approach to modelling uncertainty, based on the use of probability to describe the likelihood of uncertain events and using utility to model decision-makers' attitude to risk (Belton and Stewart 2002).

PROBLEM RESOLUTION

Having compared and evaluated the alternatives through an MCDA model and examined the robustness of the findings, decision-makers now have to make their final choice of the 'most sustainable' alternative. As already noted, MCDA can yield surprising results that may need to be digested before a final decision is taken. It is important to

bear in mind that it is not the MCDA models but the decision-makers who make decisions. MCDA models are useful because they provide structure to the debate, ensuring dialogue among decision-makers, creating an audit trail of the decision process separating 'fact' from 'emotions', helping construct preferences and make value judgements explicit, showing trade-offs between conflicting objectives, creating shared understanding about the issues, generating a sense of common purpose, and, often, resolving the problem. However, MCDA cannot give 'the' answer or 'the' solution. It is up to the decision-makers to make as much use of these features of MCDA, but in the end, it is they who will take the final decision and take responsibility for it.

Taking the final decision could be the end of the decision-making process where the actions for implementation and monitoring of its effectiveness are specified and carried outwith this process. This may be the case in operational types of decisions in corporate decision-making, where implementation of the plans of action may be delegated to a group of people who may not have participated in the decision process. However, in some situations, there may be a need for decision-makers to be involved in the translation of the outcome of decision analysis into specific plans of action and to monitor their implementation. Strategic decisions in both corporate and public policy-making may require this and a subsequent evaluation of the success of implementation.

Finally, it is important to bear in mind that decision-making is not simply a technical process which reduces down to the choice of the right MCDA technique. The success of the decision-making process will depend on many factors, but most of all on effective design of social processes within which the technical analysis is structured and conducted. By its nature, MCDA is an open and consultative process and can only be successfully implemented in social structures that are based on and support deliberative and discursive approaches to decision-making.

CONCLUSIONS

Decision-making problems in the context of sustainable development must be approached in

an integrated and systematic way. The multiple criteria decision-support framework proposed in this paper takes such an approach with the aim of facilitating both corporate and public policy decision-making. The framework can be used in situations with single or multiple decision-makers who need to reach either a strategic or operational type of decision. It can guide the decision-making process by providing structure to the debate, ensuring communication among decision-makers, and showing trade-offs between decision criteria based on the decision-makers' preferences elicited in the process. Multiple Criteria Decision Analysis (MCDA), which is an integral part of this framework, provides a set of useful methods and techniques to facilitate preference modelling. Although the choice of the 'right' MCDA technique will depend on the type of decision problem, the value-based and outranking approaches appear to be most widely used in strategic decision situations, while multi-objective optimisation and goal programming have found wider application in operational types of decision. However, regardless of the method chosen, it is important to bear in mind that it is neither the MCDA models nor the decision-support frameworks but the decision-makers who make decisions. It is therefore important that all decision-makers fully understand the process in which they are participating as, in the end, the output of decision-making is only as good as the input into it. This decision-support framework may facilitate 'good' decision-making by helping decision-makers to understand better the decision problem and the consequences of their decision for sustainable development.

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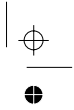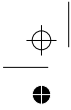
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