A Decision Support System for Ranking Countermeasures for Radionuclide Contaminated Aquatic Ecosystems: The MOIRA* project

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Abstract

This paper describes the evaluation module in the MOIRA system, which is a decision support system based on a multi-attribute additive value model, aim at the identification of optimal remedial strategies restoration of aquatic ecosystems contaminated by radionuclides. It includes facilities for assessing imprecise scalar utility functions and scaling factors, as well as a sensitivity analysis tool to check the sensitivity of the conclusions to the inputs, to allow the decision makers to gain insights into the problem. An example based on real data illustrates the usefulness of the system.

1   Introduction

The aim of the MOIRA project is to construct a model-based computerised system for the identification of the optimal remedial strategies to restore radionuclide contaminated fresh water environments. Intervention options are wide-ranging, from chemical treatment of water bodies to fishing bans or restrictions to the movement of communities. Potential actions can be broadly grouped into three categories, chemical, physical and social. In some cases, a combination of actions may be the optimal strategy. Yet another option would be not to take any remedial action.

The selection of the optimal strategy should be based on all relevant information, with the overall objective of minimizing the impact of contamination, not only from a radiological point of view, but also taking into account other important environmental, social and economic effects that the decision could entail. The MOIRA sy-

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stem incorporates a GIS database together with a complete set of reliable, validated models to predict temporal behaviour of radionuclides in the freshwater environment and the ecological, social and economic impacts. As part of the system, we have developed an evaluation module (see Gallego et al. 1998 and Ríos Insua et al. 1999, for preliminary versions), which facilitates decision making about the intervention strategies, where the basic methodology is decision analytic (French 1986). Preliminary studies suggest little uncertainty in policy effects, so we have considered our problem under certainty and use a multi-attribute additive value model (Keeney/Raiffa 1976) to rank strategies. Since the assessment of scaling factors and component values is far from easy, we use sensitivity analysis (SA) methods to alleviate this task (Ríos-Insua et al. 1998), allowing decision makers (DM) to gain insights into the problem. The methodology has been implemented in a PC based Decision Support System (DSS) which allows the incorporation of all relevant information in the process. This paper provides a description of the evaluation module of the MOIRA system, with emphasis on its implementation. It includes six more sections. In Section 2, we provide a general decription of MOIRA system. In Section 3, we structure the objectives via a hierarchy to allow the disaggregation of this complex problem into components. Section 4 provides the procedures for the weights and values/utilities assessment and, Section 5 the overall evaluation process of the chosen strategies. In Section 6, we describe some of the facilities of the SA tool and, finally, some conclusions are given.

2   The evaluation module in MOIRA system

The MOIRA system integrates several modules as it is shown in Figure 1. Each node represents a module and they are linked by branches which show relationships among them. On the one hand, we have modules that lead to obtain consequences or
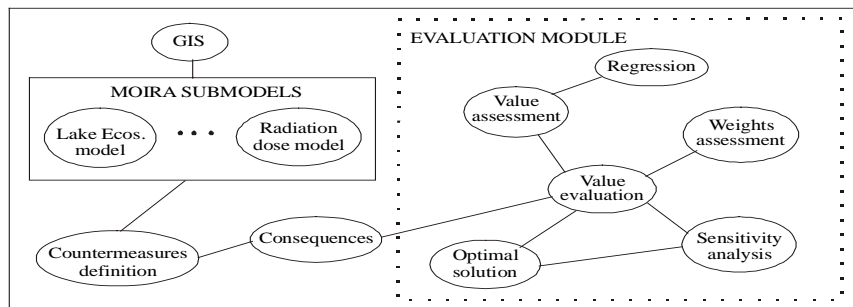

Figure 1
Modules in the MOIRA system

impacts of each strategy. Among them, we have the different modules which correspond to the submodels developed by the MOIRA collaborators, like the dose mo-

dule which estimates individual and collective effective doses in case of radioactive contamination of a water body (Jiménez/Gallego 1996) or the lake ecosystem module (Håkanson 1997). On the other, we have the Decision Analysis (DA) submodules which globally compose the evaluation module, the main objective of this paper. Those include submodules for regression analysis, utility and weight assessment, from which we obtain the evaluation of consequences to reach an optimal solution with the aid of a submodule which permits to conduct sensitivity analysis.

3   The structuring of objectives and attributes

We shall show the different evaluation submodules through a simplified real example, to demonstrate the possibilities of MOIRA. The site chosen is lake Øvre Heimdalsvatn, located in Oppland county (Norway). It is a small subalpine lake with mean depth of 4.7 m, maximum depth 13 m, surface area of .78 km^2, and catchment area of 23.6 km^2. The highest point of the catchment is 1843 m a.s.l. (meters about sea level), while the lake itself is at 1090 m a.s.l. The mean annual precipitation is 800 mm. This lake has been thoroughly studied (Vik 1978). After the Chernobyl accident, the lake was contaminated with a fallout of 130 kBq/m^2 of ^{137}Cs, which, in principle, required no countermeasures. Also, the low utilisation of the lake by people makes individual and collective doses very low, and any countermeasures resulted not to be cost-effective, since the doses that could be averted were always very low. However, an analysis of some alternative strategies have been made with the objective of testing MOIRA and its evaluation procedure for next applications.

Once defined and characterized the contaminated site, the next step is the construction of a tree of objectives, which, for this specific case, must be a simplification of the more general hierarchy tree that the system includes (Ríos Insua et al. 1999). Obviously, the three general objectives, minimizing the environmental, social and economic impacts, will be maintained for any given scenario for which MOIRA can be applied. But taking into account the peculiarities of each case, these objectives can be split in more or less branches of subobjectives, with attributes for the lowest level of the tree. The first display of the evaluation module is an objectives hierarchy with "overall impact" in its root, from which stem the three above lower level objectives and again from these stem other subobjectives until seventeen attributes arise in lowest level as the leafs of the tree. Hence, there is a graphical interface with the whole objectives hierarchy. By means of the mouse, the users may choose relevant objectives and attributes for the aquatic ecosystem under study, from node activation/deactivation along the whole tree.

For the particular case under study, the objectives hierarchy is the one shown in Figure 2. Given the low level of contamination, there will be no threat to biota, and environmental impact can be identified with the ecosystem health, which can be measured by the so called Lake Ecosystem Index (LEI) (Håkanson 1993), for which we take as attribute the *average improvement in LEI (X_1)*, along the evaluated period (6 years).
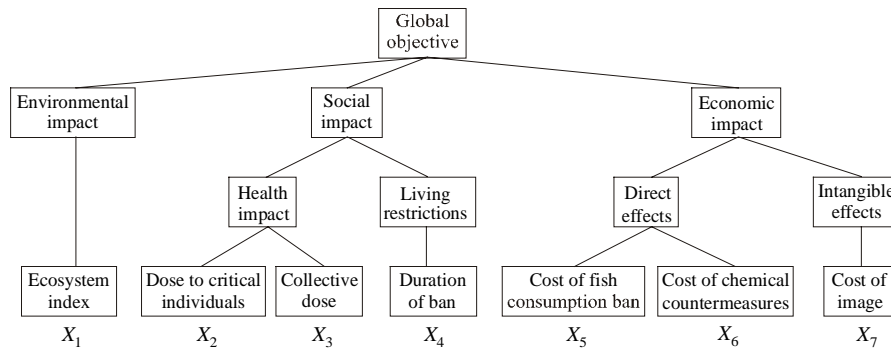
Figure 2
Objectives hierarchy for the lake Øvre Heimdalsvatn

As social impact is concerned, there are two important objectives: minimizing impact on health and on living conditions. The radiation dose is an obvious factor affecting health; in our case, we focus on *dose to critical individuals (X_2)*, -which should never receive levels above thresholds for early health effects- *and collective dose (X_3)*, which induces a linear increase in the risk of developing serious latent effects, mainly cancer. Less specific reassurance and stressing effects have been considered not significant for this case, given the fact that there is no permanent population in the area. In the living restrictions branch, the only action considered effective for this case is fishing ban, which may reduce dose by ingestion. The duration in *months of the ban (X_4)*, has been taken as a representative attribute.

Finally, the economic impact will be decomposed into intangible effects, linked to *cost-of-image (X_7)*, and adverse market reactions for the affected area, and direct effects, more amenable of economic quantification, like those associated to *a cost of fish consumption ban (X_5)*, or to *application of chemical countermeasures (X_6)*. The economic impact of a fish ban is a sum of the cost of the fish banned for consumption and the subjective cost of lost recreation. For chemical countermeasures, the implementation cost is well-known. Note that we have separated both costs because there is a subjective component in the first one, that should give different preference measures, through their respective utility functions.

The attributes for each lowest-level objective will be used as a measures of effectiveness of each strategy. They can be measured either in natural or constructed scales. For all attributes except (X_7), we consider natural scales. In the case of attribute X_7, cost of image, we introduced a constructed scale with key points defined to convey its meaning to individuals. Table 1 shows the above attributes, which also includes their units and relevant ranges, obtained for the alternatives analyzed later in our case.

Attribute	Measure	Worst (x_{i*})	Best (x_i^*)
X_1	%LEI	0.00	21.20
X_2	microSv	2.47	0.76
X_3	mSv×man	72.30	20.30
X_4	months	36.00	0.00
X_5	kSEK	426.00	0.00
X_6	kSEK	702.00	0.00
X_7	Constructed scale	100.00	0.00

Table 1
Attributes and their ranges

We then identify feasible strategies, including the no-action option, and describe their impacts in terms of each attribute. With that aim, a set of nine strategies has been analyzed, combining chemical countermeasures (addition of lime or potash at the beginning of July each year, with 40 tonnes the first year and 25 tonnes the next five; fertilization of the lake with .1 tonnes of phosphorus per month from May to October during six years) with fish banning (during the first year after the accident). They are listed in Table 2, together with their impacts. Table 2 also summarizes the results of running the MOIRA submodels for each strategy (see Monte et al. 1997, for a full description).

Countermeasures		Attributes						
Strategy	Description	X_1	X_2	X_3	X_4	X_5	X_6	X_7
S_1	No action	0	2.47	72.3	0	0	0	50
S_2	Fish banning (1st year)	0	2.18	63.7	12	142	0	75
S_3	Fish banning (2nd, 3rd and 4th year)	0	.88	23.5	36	426	0	100
S_4	Lake limming	17.5	2.34	68.3	0	0	141	25
S_5	Limming+ Fish banning (3 years)	17.5	.87	23.1	36	426	141	100
S_6	Potash treatment	15.7	2.04	59.5	0	0	702	25
S_7	Potash+ Fish banning (3 years)	15.7	.76	20.3	36	426	702	100
S_8	Fertilizing	21.2	2.45	71.5	0	0	125	25
S_9	Fertilizing+ Fish banning (3 years)	21.2	.88	23.3	36	426	125	100

Table 2
Strategies and their impacts

4 Utility and weight assessment

As a result of the screening process, there will be several remedial countermeasures available for possible implementation. The next step involves evaluation of each of these strategies through a multi-attribute value model, to help identify the best one. Each strategy S_q will be characterised by its evaluations $(x_1,..., x_7)$ in the seven relevant attributes. We rank the alternatives with a multiattribute value function, which combines multiple evaluation measures into a single measure or value of each

$$v(S_q) = \sum_{i=1}^{l} w_i \cdot v_i(x_i^q)$$

strategy. The functional form we use in MOIRA is additive, that is where x_i^q is the specific level of X_i for alternative S_q. For reasons described in (Raiffa 1982) and (Stewart 1996), we consider the above function as a valid approximation. To determine such function we need to specify:

1) Component value functions v_i for each evaluation measure;

2) Weights or scaling factors w_i, for each component value function.

We describe next some specifics of the assessment of v_i and w_i , a process which has been automated.

4.1 Utility assessment

The method to determine the component value or utility functions v_i is based on the combination of two slightly modified standard procedures for utility assessment. Several authors (e.g. Hershey et al. 1982, Jaffray 1989 or McCord/de Neufville 1986), have suggested that, in general, elicited value/utility functions are method-dependent, and bias and inconsistencies may be generated in the elicitation process. To mitigate such problems we use two methods jointly: the *fractile method* which belongs to the class of certainty equivalent methods and the *extreme gambles method* included in the probability equivalent methods (Farquhar 1984) (with these procedures, we have provided for each attribute a utility function instead of a value one. However, recall that every utility function is a value function, but not conversely). Moreover, instead of demanding only one (precise) number in each probability question, as these methods require, we allow DMs to provide a range of responses. This is less stressful on experts, since we allow them to provide incomplete preference statements by means of intervals rather than unique numbers (von Nitzsch/Weber 1988 and Ríos et al. 1994). The system uses graphical representations (coloured fortune wheel based) of the assessed utility ranges to test consistency. It suggests possible inconsistencies and the possible adjustments for the values that need to be reelicited by the DM. A library of standard utlity functions may be used by nonexperts in the evaluation process.

In consequence, we obtain a class of utility functions, rather than a single one, for each method. To detect inconsistencies we compare the responses given by both methods. There will be inconsistencies if the intersection area obtained from both types of responses were empty in some range of the attribute and we should reassess

the preferences. These reassessments finish once the DM provides a consistent range for the utility function and thus the intersection will be the range for the DM's utility functions, i.e., the elicited value or utility intervals, see Figure 3. They were obtained from both methods: for three probability levels p^1=.25, p^2=.50 and p^3=.75, with the fractile method and for attribute levels

$$x_i^I = \tfrac{1}{4}\left(x_{i*} + x_i^*\right), x_i^{II} = \tfrac{1}{2}\left(x_{i*} + x_i^*\right), x_i^{III} = \tfrac{3}{4}\left(x_{i*} + x_i^*\right)$$

for the extreme gambles method. Table 3 shows the value elicited intervals for attribute X_5. For attributes with subjective scales, utilities may be introduced directly by hand on a 'thermometer' scale.

Attribute	x_5^I	x_5^{II}	x_5^{III}
Amount	106.3	213	319.5
Utility	[.72,.80]	[.50,.55]	[.24,.29]

Table 3
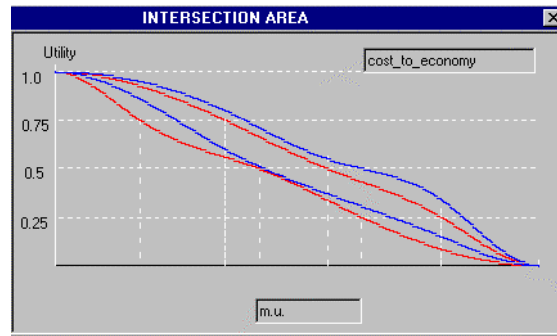
Elicited utility intervals for attribute X_5

Figure 3

Intersection between the imprecise assessment methods for attribute X_5

Once with the assessments, because the evaluation process demands precise utility functions for the evaluation of the strategies, the system provides fitted utility functions by taking the mid-points of the utility intervals of the intersection area for each v_i and then fitting natural cubic splines to such data points, see Figure 4.
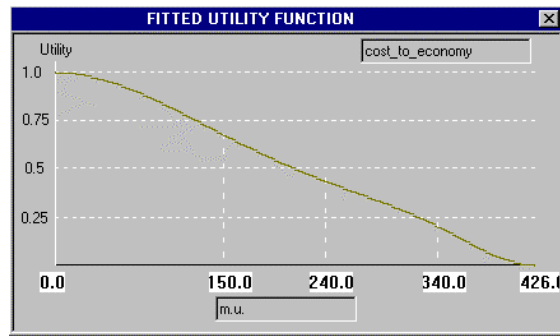
Figure 4
The fitted utility function

4.2 Assessment of weights

To have the additive value function, we need also the positive weights w_i, that allow us to add the separate contributions of the seven attributes to obtain the total utility. Hence, we have included a facility to assess such weights, that will be used also to assign weights to the higher level objectives. This will permit a global SA for the DM, allowing the intervention on any level of hierarchy of objectives.
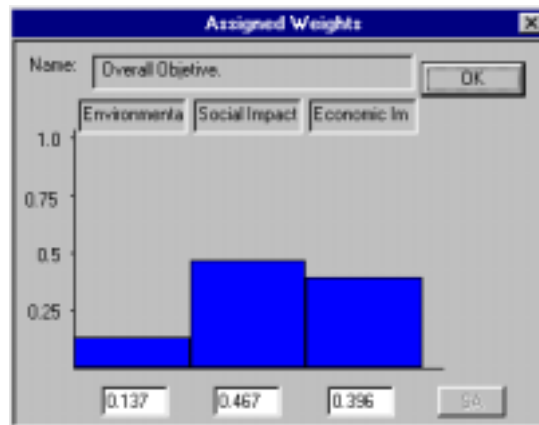

Figure 5
Watching weights for the first level objectives

We assess weights in a direct way or based on trade-offs (Keeney/Raiffa 1976), among the corresponding attributes of lowest-level objectives stemming from the same objective. We begin with the attributes and then continue the assessment in as-

cending order of the hierarchy. As in the case of utility elicitations, we assume imprecision allowing the DM to provide an interval, rather than a unique value and the system computes the corresponding precise weights, see Figure 5, and the (precise) normalized average intervals and weight intervals for attributes and objectives, see Table 4. The starting point is equally weighted objectives, but any interval weight or precise weight may be changed and the system cares for how these changes must be propagated in the objectives hierarchy and recalculates the overall utility for each strategy.

The normalized weight intervals together with the value intervals will be used in SA, on one hand, to gain insight and confidence in the ranking of countermeasures and, on the other, on aid in reducing if possible the set of countermeasures.

Attributes	k_i	$[k_i^L, k_i^U]$		Objectives	k_i	$[k_i^L, k_i^U]$
X_1	1	[1,1]		Environm. impact	.137	[.091,.182]
X_2	.328	[.245,.410]		Social impact	.467	[.389,.545]
X_3	.672	[.575,.768]		Economic impact	.396	[.296,.495]
X_4	1	[1,1]		Health impact	.689	[.626,.751]
X_5	.272	[.233,.310]		Living restrictions	.311	[.221,.400]
X_6	.728	[.647,.808]		Direct effects	.661	[.587,.734]
X_7	1	[1,1]		Intangible effects	.339	[.271,.407]

Table 4

Normalized average intervals and weight intervals for attributes and objectives

5   The evaluation of countermeasures

Given a strategy S_q with consequences

$$\mathbf{x}^q = (x_1^q, x_2^q, ..., x_7^q)$$

the global function takes, after substitution, the form

$$v(x_1^q, x_2^q, ..., x_7^q) = .137 \cdot v_1(x_1^q) + .106 \cdot v_1(x_2^q) + .216 \cdot v_1(x_3^q) + .145 \cdot v_1(x_4^q) +$$
$$+ .072 \cdot v_1(x_5^q) + .190 \cdot v_1(x_6^q) + .134 \cdot v_1(x_7^q)$$

where the attribute weights are obtained by multiplying the respective weights of the objectives of each path from the root (global objective) untill each leaf (attribute). The evaluation of the set of strategies is automatically done and their ranking. For the first strategies, the system provides a graphical representation with bars, with length proportional to their value and including their overall utilities, see Figure 6.

In our case there is a pair of strategies with close values: S_9 fertilizing combined with a fish ban for the *2nd, 3rd* and *4th* years after the accident and S_8 fertilizing.
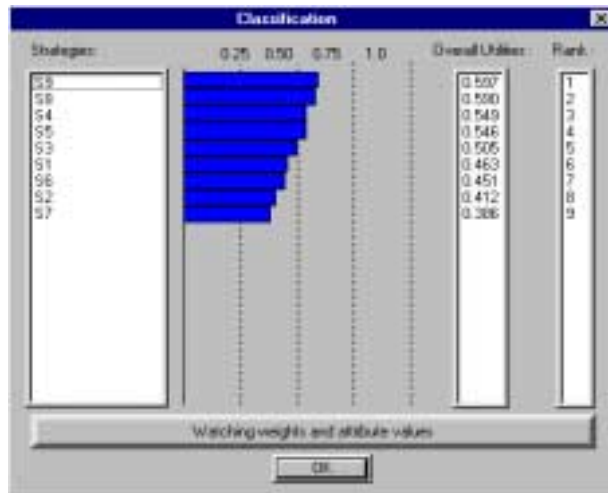
Figure 6
The ranked strategies with their utilities

Liming S_4 and liming with fish ban S_5 are also very close to this group ahead, while S_3, a fish ban for 3 years and S_6, potash treatment, have very close values between
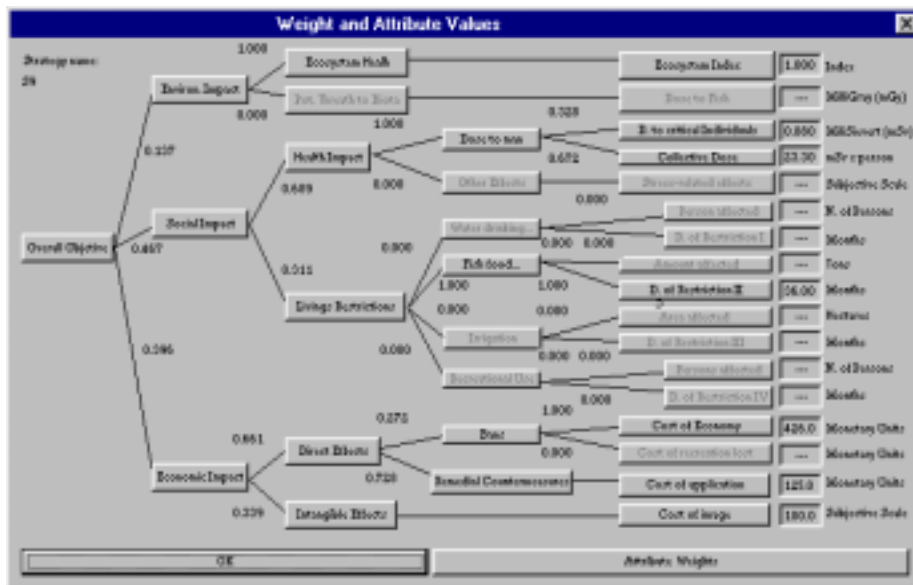

Figure 7
The objectives hierarchy with the weights for the active nodes and attribute values
for strategy S_9

them, slightly lower than the previous group. Next, we have S_1, no action, which results more preferred than S_2, short fish ban for the first year, and S_7, potash with fish ban, is the less preferred option, due to its overall low efficiency.

It is also possible to watch, by clicking on each strategy, the objectives hierarchy with the assigned weights on each upper level objective. The display contains too the values of the considered strategy with respect the active attributes, including their units, see Figure 7.

Another display shows the average weights which are associated to each one of the attributes, obtained from the weights of upper level objectives, which have been used as precise weights in the global additive utility model.

6 Sensitivity analysis

MOIRA evaluation module includes a SA facility to gain additional insight about the ranking of countermeasures. To sum up, the evaluation process computes the utility of each strategy S_q described by a vector x^q and its utility in each attribute, by means of the additive utility function. Component functions were assessed from two methods (the fractile and the extreme gambles methods), providing a class of utility functions, defined by

$$v_i^1\left(x_i^I\right)\in\left[v_i^{1L},v_i^{1U}\right]v_i^2\left(x_i^{II}\right)\in\left[v_i^{2L},v_i^{2U}\right]v_i^3\left(x_i^{III}\right)\in\left[v_i^{3L},v_i^{3U}\right]$$

which will be donoted by $v\in V$ and ranges on the weights defined by

$$k_i^j\in\left[k_i^{jL},k_i^{jU}\right]$$

denoted by $k\in K$. Thus, we have imprecise utilities and weights and they will be used in SA to gather information and help the DM to select a strategy with more confidence.

The usual way of performing SA consist of changing the weights or utilities and observe their impact on the ranking on alternatives (see, e.g., Kirkwood 1997). Hence, if the DM introduces a change in a weight or in the normalized weight range, the system cares for how these changes must be propagated in the objectives hierarchy and recalculates the overall utility for each strategy. To do so, we provide how these changes must be propagated in the objectives hierarchy and how to recalculate the overall utility for each strategy.

The above SA is useful but little systematic to aid the DM. It provides also a lot of useful information that could be exploited. Essentially, through rough calculations, we may determine some more constraints on weights and utilities, to be added to the constraints on utilities and weights. Then, they may be used in computations described in Ríos-Insua (1990) and Ríos Insua/French (1991), to eliminate definitely bad strategies, mainly discard dominated strategies and/or non potentially optimal. For that, let us rewrite

$$v(S_l) = v(S_l, k, v)$$

and if x^q is the consequence for strategy S_q and if x^l is the consequence for S_l, we will check whether strategy S_l dominates S_q, by solving the optimization problem

$$\min f_{ql} = v(S_l, k, v) - v(S_q, k, v)$$
$$s.t.$$
$$k \in K, v \in V$$

If the optimal value $f_{ql}^*>0$, then S_l dominates S_q and we discard strategy S_q. The main thrust of the above problem is to order the alternatives in a Pareto sense. Table 5 shows optimal values of those problems that need to be solved, a dash meaning that the problem needs not be solved. We see that the set of nondominated strategies is $\{S_2, S_4, S_6, S_8, S_9\}$, discarding the dominated strategies S_1, S_3, S_5 and S_7.

	S_8	S_4	S_5	S_3	S_6	S_1	S_7	S_2
S_9	-.281	-.278	.008	.014	-.173	-.214	.0828	-.1524
S_8		-.011	-	-	-.0379	.029	-	-.0011
S_4			-	-	-.0305	-	-	-.0111
S_5				-	-.250	-	-	-.2871
S_3					-.379	-	-	-.2806
S_6						-	-	-.0378
S_1							-	-.0289
S_7								-.2078

Table 5
Optimal values f_{ql}^*

These results imply that, for the assessed scenario, no action S_1 is dominated by fertilizing of lake S_8. On the other hand, strategy combining the fertilization plus fish banning S_9 dominates the other three with fish banning along all the period S_3, liming S_5 and potash treatment S_7. Therefore, fish banning all the period S_3 and chemical strategies combined with fish banning, S_7 and S_5, as well as no action S_1, can be discarded. This conclusion was not apparent from Table 2, as it is dependent on the ranges given for component utilities and weights.

The system can also determine potentially optimal (p.o.) strategies among the nondominated ones. It may be an aid to propose as solutions those strategies S_j that maximize $v(S_j, k, v)$ for some $k \in K$ and $v \in V$. The system may compute too the adjacent optimal alternatives, i.e., those that may share optimality with S^*. From both concepts, we should reduce the set of strategies of interest to the set $\{S_4, S_6, S_8, S_9\}$.

Finally, MOIRA computes the utility intervals for the remaining strategies. These are obtained for each strategy S_q as the utility maximum variation intervals, from the usual restrictions on SA, obtaining

$$\left[v^m(S_q), v^M(S_q)\right] = \left[min_{k \in K, v \in V} v(S_q), max_{k \in K, v \in V} v(S_q)\right]$$

For our problem, the utility intervals as well as their ranges for the rest of strategies, are shown in Table 6.

Strategy	$[v^m(S_q), v^M(S_q)]$	Range
S_4	[.336,.887]	.551
S_6	[.286,.763]	.477
S_8	[.350,.889]	.539
S_9	[.367,.887]	.520

Table 6
Utility ranges for the selected strategies

In Figure 8, we have drawn another output of the system. We have horizontal bars which indicate for each strategy its utility interval and on each bar appears a small vertical line pointing out the precise utility before obtained. In our case, it seems clear that we could eliminate S_6, but the other strategies looks similar.
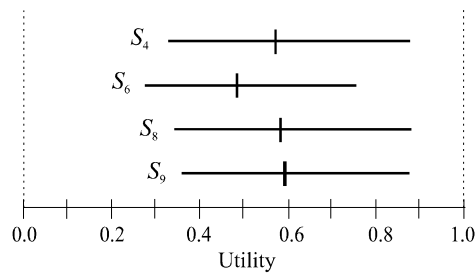

Figure 8
Utility intervals with indication of the precise value (small vertical line) for the selected strategies

Thus, we should have one more procedure which, with the above ones, should constitute a set of tools to aid the DM in choosing the final strategy.

7 Conclusions

We have applied Decision Analysis methods to construct the evaluation module in MOIRA, a DSS to identify optimal remedial strategies for restoring water systems. It is intended for use in case of accidental introduction of radioactive substances into an aquatic ecosystem and its drainage areas. Countermeasures are then evaluated and ranked from an additive multi-attribute value/utility model which represent the experts' preferences. Moreover, we introduce the possibility of multiparametric sensitivity analyses with respect to weights and values of DMs, to aid them in choosing a final strategy. For that, we apply some concepts which permit us to reduce the set of strategies of interest and assess robustness of solution and, eventually, elicit additional information from the DMs.

The methodology described is implemented in a PC based DSS and allows the incorporation of all relevant information in the process, including imprecision on values.

Acknowledgments

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