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Abstract

This paper presents a Multi-Attribute Decision Support System aimed at aiding decision-makers in identifying optimal alternatives in complex decision-making problems. The system is based on a multi-attribute additive value model and admits imprecise assignments concerning weights and utilities and uncertainty about the multi-attribute alternatives. Different sensitivity analyses are possible over the inputs permitting the users to test the robustness of the alternative ranking to gain insight on the final solution. Specifically, Monte-Carlo simulation techniques are performed, which allows simultaneous changes on weights and whose results can be statistically analyzed.

An application to the restoration of a radionuclide contaminated aquatic ecosystem is illustrated throughout the paper.

Key Words

1. Introduction

Many complex decision-making problems have multiple conflicting objectives, having to take into account preference trade-offs between differing degrees of achievement of one objective and another. Also, real problems are usually plagued with uncertainty and it is impossible to predict with certainty what the consequences of each alternative under consideration will be. Thus, a formal analysis is required because it is very difficult to consider the above complexities informally in the mind.

The goal of decision analysis (DA) is to structure and simplify the task of making hard decisions as well and as easily as the nature of decision permits, [1]. DA is concerned with multiple conflicting objectives for many complex, real-world decision-making problems and is developed on the assumption that the alternatives will appeal to the expert, depending on:

- the likelihood of the possible consequences of each alternative,
- expert's preferences concerning the possible consequences.

What makes DA unique is the form in which these factors are quantified and formally incorporated into the problem analysis. Existing information, collected data, models and professional judgements are used to quantify the likelihood of a range of consequences, while utility theory is used to quantify preferences, [2].

In this paper we introduce a PC-based Decision Support System (DSS) based on the DA cycle, [3,4], aimed at aiding decision-makers (DMs) in identifying the optimal alternative and that is intended to allay many of the operational difficulties involved in assessing and using multiattribute utility functions.

The system admits imprecise assignment for single utilities, which represent the DM's preferences concerning the possible alternative consequences, and weights, which represent the relative importance of criteria in the objects hierarchy that models the decision-making problem.

On the other hand, the system accounts for uncertainty about the alternative consequences by means of uniformly distributed value intervals instead of single values.

The alternative evaluation is performed by means of an additive multi-attribute utility function, which leads to an alternative ranking based on the average overall utilities. However, as the system admits imprecision concerning single utilities and weights, and uncertainty about the alternative consequences, lower and upper overall utilities are output as well.

A sensitivity analysis (SA) tool is included for testing the robustness of the alternative ranking and gaining insight into and confidence about the final solution.

The usual way of performing SA involves examining changes in the ranking, as a function of the input parameters (weights, single utilities and/or alternative consequences) varying within a reasonable range.
Also, the system computes non-dominated and potentially optimal alternatives, taking advantage of the useful imprecise information entered.

Finally, the system performs simulation techniques for SA. This kind of sensitivity analysis, see [5,6], uses Monte-Carlo simulation and allows simultaneous changes on weights. Generated results can be easily analyzed statistically to provide more insights into the multiattribute model recommendations.

We propose selecting weights at random using a computer simulation program so that the results of many combinations of weights, including a complete ranking, can be explored efficiently. Three general classes of simulation will be presented: random weights, rank order weights and response distribution weights. We illustrate throughout the paper an application example, the restoration of a radionuclide-contaminated aquatic ecosystem. The considered scenario is lake Øvre Heimdalsvatn, located in Oppland County (Norway). This problem has been studied in depth in two European Projects in which we have participated: MOIRA (A MOdel-based computerized system for management support to Identify optimal Remedial strategies for restoring radionuclide contaminated Aquatic ecosystem and drainage areas) and COMETES (Implementing COMPUTERized Methodology to Evaluate the effectiveness of countermeasures for restoring radionuclide contaminated fresh water ecoSystems), see [7,8].

The next section deals with the DA steps, the way they are considered in the PC-based DSS and their application to the restoration problem. Section 3 describes the SA tools included in the system. Specifically, we shall pay attention to the simulation techniques for SA. Finally, in section 4 some conclusions are provided.

2. Decision Analysis cycle in a PC-based DSS

Let us divide DA into four steps:

- structuring the problem (which includes building a value hierarchy, specifying objectives and attributes for the lowest-level objectives),
- identifying the feasible alternatives, their impact and uncertainty (if necessary),
- quantifying preferences (which includes the assessment of single attribute utility functions, as well as value trade-offs), and
- evaluation of alternatives.

2.1 Structuring the problem

There are several benefits to be gained from using a hierarchy to model complex decision-making problems with multiple objectives. For instance, it helps to ensure that there will be no big gaps (missing objectives) at lower levels, situations where redundancy or double-counting could easily occur can be identified and it provides a basis upon which to develop and appraise screening criteria ([9]).

Figure 1 shows the hierarchy constructed by the experts for the lake restoration problem, which displays four levels and seven lowest-level objectives. Note that due to the system flexibility, it will be possible to add or to drop a node at any time if deemed.

The default weights associated with nodes stemming from the upper-level objective will be equal, and the sum of these weights will, of course, be 1.

![Objectives hierarchy for the restoration problem](image)

Figure 1. Objectives hierarchy for the restoration problem

The main purpose is minimizing the overall impact of radioactive contamination affecting the aquatic ecosystem, by the application of appropriate remedial alternatives. To evaluate the most preferable alternative, this objective can be split into three, concerning the environmental, social and economical impact caused by any alternative analyzed.

In [8] we can see a description of the objectives at different levels of this hierarchy and the role they play in the restoration problem.

DA involves establishing attributes associated with the lowest-level objectives to indicate to what extent they are achieved by the considered alternatives. For, some basic properties related to the set of attributes see [2].

Table 1 shows the considered attributes, which also includes their units and relevant ranges.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Measure</th>
<th>Worst level</th>
<th>Best level</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1: Lake Ecosystem Index</td>
<td>%LEI</td>
<td>5.0</td>
<td>1.0</td>
</tr>
<tr>
<td>X2: Dose to critical individuals</td>
<td>microSv</td>
<td>2.47</td>
<td>0.76</td>
</tr>
<tr>
<td>X3: Collective dose</td>
<td>mSv/man</td>
<td>72.3</td>
<td>20.3</td>
</tr>
<tr>
<td>X4: Duration of bans</td>
<td>months</td>
<td>36</td>
<td>0</td>
</tr>
<tr>
<td>X5: Cost to economy</td>
<td>euro×100</td>
<td>426</td>
<td>0</td>
</tr>
<tr>
<td>X6: Cost of application</td>
<td>euro×100</td>
<td>702</td>
<td>0</td>
</tr>
<tr>
<td>X7: Cost of image</td>
<td>Subj. Scale</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

2.2 Identifying the feasible alternatives

Next, feasible remedial alternatives must be identified and we have to establish how to measure these alternatives in terms of attributes.
As mentioned above, the system accounts for uncertainty about the alternative consequences by means of uniformly distributed value intervals instead of single values. Thus, given an objectives hierarchy with attributes $X_i$, $i=1,...,n$, associated with the lowest-level objectives, the consequences of a remedial alternative $S_j$ can be described under uncertainty by a vector of ranges

$$
\left( [x_{ij}^{L}, x_{ij}^{U}],..., [x_{jL_n}, x_{jU_n}] \right),
$$

where $x_{ij}^{L}$ and $x_{ij}^{U}$ are the lower ($L$) and upper ($U$) levels for attribute $X_i$.

In our example, a set of nine remedial alternatives has been analyzed, combining chemical countermeasures with fishing ban so as to reduce the radiological and environmental impact, see Table 2.

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>No Actions</td>
</tr>
<tr>
<td>S2</td>
<td>Fishing Ban (1st year)</td>
</tr>
<tr>
<td>S3</td>
<td>Fishing Ban (2nd, 3rd and 4th year)</td>
</tr>
<tr>
<td>S4</td>
<td>Lake Liming</td>
</tr>
<tr>
<td>S5</td>
<td>Liming + Fishing Ban (3 years)</td>
</tr>
<tr>
<td>S6</td>
<td>Potash Treatment</td>
</tr>
<tr>
<td>S7</td>
<td>Potash Treatment + Fishing Ban (3 years)</td>
</tr>
<tr>
<td>S8</td>
<td>Fertilization</td>
</tr>
<tr>
<td>S9</td>
<td>Fertilization + Fishing Ban (3 years)</td>
</tr>
</tbody>
</table>

Another important feature of the developed system is that alternatives with missing consequences, that is, alternatives that do not provide values or consequences for some attributes in the hierarchy, are allowed. When evaluating the alternatives under consideration, the system will take them into account by adequately redistributing the attribute weights of these attributes for which no consequence has been provided among the remainder. However, in our lake restoration example there are not alternatives with missing consequences, i.e., uniformly distributed consequence intervals are entered for all attributes.

2.3 Quantifying preferences

Quantifying preferences involves assessing the DM's single attribute utilities, which represent the DM's preferences concerning the possible alternative consequences, and weights, which represent the relative importance of criteria in the objectives hierarchy. Both will be used later to evaluate the alternatives through a multi-attribute utility function. As mentioned above, the system admits imprecision in the assignment process.

Single utilities can be assigned using four procedures depending on the level of knowledge and features of the attribute under consideration. First, the system provides a method based on the combination of two slightly modified standard procedures for utility assessment: the *fractile method* and the *extreme gamble method*, see [10]. The DM is allowed to provide incomplete preference statements to the probability questions he is faced, by means of intervals rather than single numbers ([11,12]).

When there is a deep and precise knowledge about the attribute, the DM can construct a piecewise linear utility function, see Figure 2.

The third procedure consists of the assignment of imprecise utilities for several available discrete attribute values.

Finally, the DM can decide to use subjective values for one or more attributes of the tree instead of a utility function or imprecise utilities for discrete attribute values (*Cost of Image*, in our example). In this case, ranges of subjective values are entered manually through scrollbars, see Figure 3.

With respect to the weight elicitation, the system provides two methods, direct assignment and weight elicitation based on trade-offs. Note that imprecision concerning the DM's responses is allowed in both.

The *direct assignment* is perhaps more suitable for upper level objectives that can be more political. The DM has to provide a weight interval for each sub-objective under consideration.

The second procedure is based on *trade-offs* among the respective attributes of the lowest-level objectives stemming from the same objective. The DM is asked to
give an interval of probabilities such that he is indifferent with respect to a gamble and a sure consequence, [2].

2.4 Evaluation of alternatives

This step involves evaluating each alternative model to help identify the best one, by means of an additive multi-attribute utility model, which takes the form:

\[ u(S_j) = \sum_{i=1}^{n} w_i u_i(x_i) = w_1 u_1(x_1') + \ldots + w_n u_n(x_n') , \]

where \( x_i' \) is the consequence of the alternative \( S_j \) for the attribute \( X_i \), \( u_i \) are the single utilities assigned to the respective attribute \( X_i \) and \( w_i \) is the weight for attribute \( X_i \), assessed by multiplying the respective weights of the objectives in the path from the root (global objective) to each leaf (attribute).

This evaluation process leads to an alternative ranking based on the average overall utilities, see Figure 4. But, note that, as the system admits imprecision concerning single utilities and weights and uncertainty about the alternative consequences, lower and upper overall utilities are output as well.

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Another way of performing SA involves assessing the stability weight intervals for the objectives in the hierarchy, in which average normalized weights can vary without affecting the overall ranking of alternatives. Figure 6 shows the stability weight interval for the Health Impact objective.

3. Sensitivity Analysis

Sensitivity analysis (SA), which essentially involves examining changes in the ranking, as a function of the input parameters (weights, single utilities or alternative consequences) varying within a reasonable range can give further insight into robustness of the recommendations. Some types of sensitivity analysis are described in [13,14], which introduce a framework for sensitivity analysis in multiobjective decision-making.

The system takes charge of how changes in input parameters are propagated through the objectives hierarchy and automatically recalculates the overall utilities for each alternative and the resulting ranking.

The system also computes non-dominated and potentially optimal alternatives. Here, we intend to take advantage of the imprecise information collected during the assignment of single utilities and weights and the entered alternative consequences under uncertainty to reject definitely bad alternatives, mainly by discarding dominated and/or non-potentially optimal alternatives. Essentially, some more constraints on weights, utilities and alternative consequences can be determined by rough calculations, [13,14], which leads to non-linear optimization problems that can be transformed into linear and solved by using the Simplex Method, see [15].

In the lake restoration problem, all the alternatives except Potash Treatment and Potash Treatment + Fishing Ban (3 years) are non-dominated and potentially optimal. Thus, these two alternatives can be discarded, see Figure 5.

Another way of performing SA involves assessing the stability weight intervals for the objectives in the hierarchy, in which average normalized weights can vary without affecting the overall ranking of alternatives. Figure 6 shows the stability weight interval for the Health Impact objective.

Note that the stability interval is [0.37, 0.415], which means that if the DM changes the present value 0.4 to any value in the stability interval, the actual ranking remains
unchanged. Otherwise, the ranking changes and is computed by the system.

Finally, the system performs simulation techniques for SA. This kind of sensitivity analysis uses Monte-Carlo simulation, see [5,6], allows simultaneous changes of the weights and generates results that can be easily analyzed statistically to provide more insights into the multi-attribute model recommendations.

We propose selecting the weights at random using a computer simulation program so that the results of many combinations of weights, including a complete ranking, can be explored efficiently. The system uses a multiplicative linear congruential generator based on Schrage's method, first published in 1979, and later refined in 1983, see [16]. It provides a virtually infinite sequence of statistically independent random numbers, uniformly distributed between 0 and 1.

Once the simulation has been run, the system computes several statistics about the rankings of each strategy, like mode, minimum, maximum, mean, standard deviation and the 25th, 50th and 75th percentiles. This information can be useful for discarding some available alternatives, aided by a display that presents a multiple boxplot for the alternatives.

Three general classes of simulation will be presented: random weights, rank order weights and response distribution weights. They are described briefly below.

**Random weights.** As an extreme case, weights for the attributes are generated completely at random. This approach implies no knowledge whatsoever of the relative importance of the attributes.

This type of analysis can be useful when attempting to identify a subset of alternatives for a more detailed analysis and in contexts with multiple DMs, each of them with a unique set of weights.

It may be possible to eliminate some alternatives from further consideration without conducting an assessment of weights.

To generate the additive weights for the \( n \)-attribute case, we first select \( n-1 \) random numbers from a uniform distribution on (0,1) independently, and then rank this numbers. Suppose that the ranked numbers are \( 1 > r_{(n-1)} > ... > r_{(2)} > r_{(1)} > 0 \). The first differences of these ranked numbers (including the bounds 0 and 1) can be obtained as:

\[
k_n = 1 - r_{(n-1)}, \]

\[
k_{n-1} = r_{(n-1)} - r_{(n-2)}, \]

\[
... \]

\[
k_1 = r_{(1)} - 0.
\]

Then, the set of numbers \((k_1, k_2, ..., k_n)\) will sum to one and be uniformly distributed.

Figures 7 and 8 show the multiple boxplot diagram and the associated statistics measures for this simulation with random weights.

As it can be seen, this type of simulation technique is not useful at all for our lake restoration problem. All the alternatives except *Lake Liming* are best ranked for at least one combination of weights. Moreover, all are worst ranked for at least one combination of weights as well. Thus, no alternative can be discarded.

**Rank order weights.** Randomly generating the weights while preserving their criteria rank order places substantial restrictions on the domain of possible weights that are consistent with the DM’s judgement of criteria importance. Therefore, the results from the rank order simulation may provide more meaningful results.

While the exact magnitude of the weights may be called into question, the relative importance ranking of the attributes may be less controversial, especially in a multiple DMs situation.

By importance ranking we are referring to a rank ordering where the highest ranked objective is the one the DM would most prefer to increase from the worst to the best level of performance. In this analysis, the weight rank order on the measures is maintained, but the weights are otherwise generated at random. Figure 9 shows the results for this simulation with the following criteria rank order:

- **Duration of Bans**
- **Cost of Application**
- **Lake Ecosystem Index**
- **Cost of Image**
- **Collective Dose**
- **Cost to Economy**
- **Dose to critical individuals**

Now, only two alternatives are best ranked, *No Actions* and *Fertilization*. However, while the worst classification of *No Action* is the seventh, for *Fertilization* is the third. Thus, *Fertilization* seems to be the remedial alternative to be performed if the above attribute ranking is taken into account.
Response distribution weights. The third type of sensitivity analysis using simulation recognizes that the weight elicitation procedure is subject to variation. For a single DM, this variation may be in the form of response error associated with weight elicitation. Thus, attribute weights are now randomly assigned values taking into account the weight intervals provided by the DM in the weight elicitation methods.

Figure 10 shows the imprecise attribute weights used in the simulation and Figure 11 the results.

Only two alternatives are best ranked, Fertilization and Fertilization + Fishing Ban (3 years), and the worst classification for both is the fifth. Thus, one of them is the remedial alternative to be performed.

4. Acknowledgement

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