Restoring a Radionuclide Contaminated Aquatic Ecosystem: A Group Decision Making Problem with Incomplete Information within MAUT Accounting for Veto

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Abstract In this paper we consider the evaluation of intervention countermeasures for the restoration of a radionuclide contaminated aquatic ecosystem, simultaneously taking into account several conflicting objectives, like environmental, social and economic impacts. We propose an extension of the additive multi-attribute utility model to incorporate the concept of veto to deal with this group decision-making problem. Moreover, we consider what is known as decision-making with partial, imprecise or incomplete information, which accounts for uncertainty about the alternative performances and imprecision concerning DM preferences by means of intervals or ordinal information. Veto values for the most important DMs are used to define veto ranges, whereas veto values corresponding to the other less important DMs are partially taken into account, leading to the construction of adjust ranges. We then build the veto and adjust functions into the additive model, and a dominance matrix accounting for incomplete information is computed. A dominance measuring method is then used to derive a ranking of alternatives for each DM, which are then aggregated taking into account their relative importance.

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1 Introduction

The additive model is considered to be a valid approach within multi-attribute value/utility theory (MAVT/MAUT) in most practical situations for the reasons described in Raiffa (1982), Stewart (1996).

However, the information available in most real complex decision-making problems is not precise. Inputs are often described within prescribed bounds or as just satisfying certain relations. Different authors refer to this situation as *decision-making with imprecise information, incomplete information or partial information* (Ríos Insua 1990; Ríos and French 1991).

Several reasons are given in the literature that justify why a decision-maker (DM) may wish to provide imprecise information (Sarabando and Dias 2010; Weber 1987). For example, performances that reflect social or environmental impacts may be intangible or non-monetary, and performances may be taken from statistics or measurements. Besides, a DM might prefer not to reveal his/her preferences in public or could feel more comfortable providing a scale to represent attribute importance.

Sarabando and Dias (2009) provided a brief overview of approaches proposed by different authors within the MAVT/MAUT framework to deal with imprecise information, including the modification of four classical decision rules to encompass an imprecise decision context on the basis of the absolute dominance notion (Puerto et al. 2000; Salo and Hämäläinen 2001), *surrogate weighting methods* (Barron and Barret 1996; Stillwell et al. 1981), in which a weight vector is selected from a set of admissible weights to represent the set, which is then used to evaluate the alternatives by means of the multi-attribute value model; *stochastic multicriteria acceptability analysis (SMAA)* (Lahdelma et al. 1998), *SMAA-2* (Lahdelma and Salminen 2001) and *SMAA-O* (Lahdelma et al. 2003), which are based on the idea of volume computations; or the assessment of dominance and potential optimality on the basis of the pairwise dominance notion (Eum et al. 2001; Lee et al. 2002; Mateos et al. 2007).

A more recent approach for dealing with imprecise information, which consists of computing different measures of dominance to derive a ranking of alternatives, are *dominance measuring methods (DMMs)* (Ahn and Park 2008; Aguayo 2014). *DMMs* are based on the computation of a *dominance matrix*, D , including pairwise dominance values, which are exploited in different ways to derive measures of dominance to rank the alternatives under consideration.

Besides, real complex decision-making problems usually take into account the preferences of a group of DMs. Many multi-attribute methods for individual decision-making have been extended to a group framework. Two different approaches for the aggregation process can be considered.

First, the aggregation process could be performed at the level of individual parameters of the decision model (component utilities and weights). For instance, Mateos et al. (2003) develop a decision support system based on Monte-Carlo simulation techniques, where the DMs' preferences are elicited separately, as a starting point

for a negotiation process. Jiménez et al. (2005) propose an iterative process in which the imprecise sets of utilities and weights corresponding to the different DMs are successively tightened.

On the other hand, the aggregation process could be performed at the level of evaluations of the considered alternatives (Vetschera 1990). Different methods for aggregating rankings by different authors can be found in the literature. Lin (2010) discusses three classes of methods, namely distribution-based methods, for instance, the original Thurstone scaling and its extensions (Green 1978); heuristic methods, ranging from simple arithmetic averages of ranks (Bordas methods) Borda (1981) to Markov chains and stationary distributions (DeConde et al. 2006); and stochastic optimization search methods, such as the Kemeny optimal aggregation (Kemeny 1959).

Finally, the *veto* concept is considered as a real-world approach for representing the limits of DM preferences, and is thus an important tool in multicriteria and group decision-making. At the same time, this use of the veto concept is an attempt to account for the flawedness or ambiguity of the evaluation of alternatives in order to reach a consensus. The veto concept has been used both in non-compensatory and compensatory methods within *multicriteria decision making* (MCDM).

The concept of veto threshold could be related within MAUT to the definition of each attribute's preference bounds, whereby alternatives whose criteria are rated above or below these bounds are rejected by DMs depending on whether their utility function is increasing or decreasing and irrespective of the value that they take for other attributes (Sabio et al. 2015). Veto could be also applied to the rankings of alternatives derived by each DM (Daher and de Almeida 2012).

In this paper we consider a complex decision-making problem, the evaluation of intervention countermeasures for the restoration of a radionuclide contaminated aquatic ecosystem, simultaneously taking into account several conflicting objectives, like environmental, social and economic impacts.

We account for a decision-making within an imprecise information context, where the impacts of the countermeasures will be described under uncertainty and imprecise preferences of several experts will be incorporated into the analysis by means of ordinal information. Moreover, experts are allowed to provide vetoes expressed in terms of alternative performances.

We propose a methodology to deal with this group decision-making problem with imprecise information accounting for veto. The methodology consists of two aggregation phases. In the first phase, the additive multi-attribute model is first adapted to account for DM vetoes by adding a veto and an adjust function. A *dominance measuring method* accounting for the imprecise DM preferences is used to derive a ranking of alternatives for each DM. Note that although the respective DMs preferences concerning weights are considered for each ranking, the resulting ranking is influenced by the opinion of the other DMs by means of the veto and adjust functions.

In the second phase, the different rankings derived in the first phase are aggregated taking into account the relative importance of DMs to reach a group ranking using the *order explicit algorithm method*, an extension of Kemeny optimal aggregation.

The paper is structured as follows. Section 2 introduces the restoration of radionuclide contaminated aquatic ecosystems problem, which is structured by means of an

objective hierarchy. Section 3 deals with group decision-making with incomplete information within MAUT. First, remedial countermeasures and their impacts in terms of the previously identified attributes are described under uncertainty by means of intervals or ordinal information. Then, DM preferences are imprecisely quantified, leading to classes of component utility functions and ordinal information about utilities/weights.

Section 4 introduces the origin of the veto concept and reviews how it was used in non-compensatory and compensatory methods within MCDM. Then, Sect. 4.1 describes an approach to deal with veto values in a group decision-making context. Section 5 proposes the methodology to deal with a group decision-making context with imprecise information accounting for veto on the basis of two aggregation phases. First, we introduce a dominance measuring method in Sect. 5.1 to derive a ranking of alternatives for each DM. We then analyze the aggregation of the resulting rankings taking into account the relative importance of DMs in Sect. 5.2. Section 6 discusses alternatives identified in the literature for incorporating veto values into the analysis, which are compared with our proposal. Finally, some conclusions are provided in Sect. 7.

2 Restoration of an Aquatic Ecosystem Contaminated by Radionuclides

The evaluation of intervention countermeasures for the restoration of a radionuclide contaminated aquatic ecosystem was studied in depth as part of several European projects in which we participated: MOIRA (Monte et al. 2000), COMETES (Monte et al. 2002), EVANET-HYDRA (Monte et al. 2005), and EURANOS (Raskob et al. 2010). Throughout these projects, a synthetic, flexible and user-friendly computerized decision support system, MOIRA (Gallego et al. 2009; Monte et al. 2009), was implemented and tested on several real scenarios.

The source term in the scenario considered in this paper was postulated after a hypothetical severe accident at the Almaraz nuclear power plant (Spain). Taking into account the level-2 PSA (probabilistic safety analysis), the release category R6 was selected (Khatib-Rahbar et al. 1998), implying quite a sizeable and relatively credible release despite the extremely low probability of such a severe accident. Specifically, a release of 3% of the Cs¹³⁷ and 0.062% of Sr⁹⁰ inventories was considered.

For this particular scenario, we focus on a wetland area of Extremadura region, Lake Palancoso, which belongs to the Ejido Nuevo lake complex, located in the district of Campo Arañuelo. While not a source of drinking water, it has notable ecological value with a status of *special protection area for birds*. On top of that, the existence of recreational fishing, while not implying high collective doses due to the low total volume, could lead to unacceptable doses for the fishermen consuming their own captures. Furthermore, the area attracts a lot of tourists, due to fishing and birdwatching, some of the birds being in danger of extinction.

Lake Palancoso has a surface area of roughly 100,000 m², whereas the catchment area is five times the size of the lake. Its depth is highly variable over the year since its volume is small, and it is situated at 270 m above sea level. Further information concerning chemical conditions at the lake, soil and weather conditions, land use, fish

Fig. 1 Objective hierarchy

production and water withdrawal for human consumption is available in Gallego and Magán (2009).

RODOS (real-time on-line decision support for nuclear emergencies) (Ehrhardt et al. 1997) simulation was performed with the postulated release. Results showed that local contamination with Cs^{137} would be between 10^4 and 10^5 Bq/m². The conservative approach was taken and thus the maximum value was chosen. Besides, Sr^{90} fallout is around 1/30 that of Cs^{137} , i.e. 3.000 Bq/m².

2.1 Structuring the Restoration Problem

An objective hierarchy was built, including all the relevant aspects to be taken into account in the restoration problem, see Fig. 1.

Environmental Impact (Environ. Impact) is one of the main objectives of the decision analysis. It is divided into *Lake Ecosystem Index* (LEI) and *Dose to Fish* (Monte and Brittain 1998). LEI is a simple, rational approach for measuring the ecological status of a lake, by comparing normal values of key variables with their actual values and their influence on the fish yield, the phytoplankton biomass and the bottom fauna biomass (Håkanson et al. 2000).

Social Impact (Social Impact) is handled by two subobjectives: minimizing impact on health, *Dose to Man*, and *Living Restrictions*. Regarding dose to man, we focus on the *Dose to Critical Individuals* and *Collective Dose*. *Dose to Critical Individuals* refers to the effective dose received by individuals belonging to a critical group living in the area, drinking water and eating aquatic food and food grown on land irrigated with water from the contaminated body of water, whereas *Collective Dose* is a measure of the increased risk of serious latent health effects.

Table 1 Attributes with continuous scale

	Unit	Range
X_1 : Lake Ecosystem Index	LEI	[1, 5]
X_3 : Dose Crit. Indiv.	mSv	[0, 500]
X_4 : Collective Dose	mSv $\times$ person	[0, 12×10^4]
X_5 : Amount of Fish	Tonnes	[0, 100]
X_6 : Ban Duration	Months	[0, 360]
X_7 : Costs to Economy	Euros	[0, 10^8]
X_8 : Application Cost	Euros	[0, 10^7]

As regards *Living Restrictions*, other impacts are taken into consideration. These include countermeasures affecting the direct consumption of fish for food or its processing in the food industry, drinking water and water used by the food industry, the use of water for crop irrigation and the recreational uses of water bodies. For all these objectives, the attributes will be the amount of fish affected by restrictions (*Amount of Fish*), as well as the duration of such restrictions (*Ban Duration*).

Finally, *Economic Impact* has been divided into *Direct Effects* (Direct Effects), more amenable to quantification, and *Intangible Effects*. The direct effects include the costs generated by the different bans or restrictions to normal living conditions, which can be sub-divided into *Costs to the Economy*, the direct economic impact of the restrictions, either in terms of the cost of the food affected by bans or in terms of loss of production (e.g., share in the fall of the gross domestic product), and *Application Costs*, i.e., direct cost of the application of chemical and physical remedial countermeasures: manpower, consumables, equipment needed for application, management of waste generated, etc.

As regards *Intangible Effects*, we consider the *Cost of Image*, which represents the indirect costs associated with the different strategies that can be perceived by the public differently due to market reluctance concerning even uncontaminated products, a drop in tourism, etc.

Next, attributes were established for the lowest-level objectives to indicate to what extent they were achieved by the respective remedial countermeasures. Table 1 shows the attribute names, units and ranges for seven out of the nine attributes under consideration using a continuous scale. Ordinal information about the component utilities of the countermeasures were considered for the remaining attributes, X_2 : Dose to Fish and X_9 : Cost to Image, as described afterwards.

3 Group Decision-Making with Partial Information

Eight different chemical, social and physical countermeasures were considered for analysis in the restoration problem under consideration:

- A_1 , A_2 : *Potassium addition* These countermeasures aim at reducing Cs^{137} intake by fish. It is based upon the fact that Cs and K intakes are chemically competitive, and thus a greater amount of K tends to reduce Cs^{137} intake. A_1 consists of a

Table 2 Countermeasure impacts

	A ₁	A ₂	A ₃	A ₄	A ₅	A ₆	A ₇	A ₈	A ₉
X ₁ : L. Ecosyst. Index	1.33	1.33	1.332	1.630	1.618	1.962	1.33	1.33	1.33
X ₃ : Dose Crit. Indiv.	43.7	41.9	45.2	44.8	41.9	44.8	20.7	1.7	45.3
X ₄ : Collective Dose	3490	3360	3630	3590	3360	3560	1690	180	3630
X ₅ : Amount of Fish	0	0	0	0	0	0	0	36	0
X ₆ : Ban Duration	0	0	0	0	0	0	0	120	0
X ₇ : Costs to Economy	0	0	0	0	0	0	0	62,300	0
X ₈ : Application Cost	2242	7830	1052	4209	11,807	38	31,56,390	0	0

single potassium treatment, whereas A₂ refers to a periodic potassium treatment (7 years).

- A₃: *Lake liming* This countermeasure aims at reducing biological intake of Cs¹³⁷ and Sr⁹⁰. It is based upon the fact that pH influences the intake of those elements, and usually the higher the pH, the lower the intake.
- A₄, A₅: *Wetland liming* This countermeasure is similar to the above but the lime is added to the whole catchment. A single (A₄) and a periodic (A₅) catchment liming are considered.
- A₆: *Fertilization* This countermeasure tries to cause a biological dilution of contamination, based upon the idea that, by increasing the biomass of the lake, the concentration of contamination in it must decrease.
- A₇: *Removal of contaminated bottom sediments* A total clean-up of the sediment was assumed to take place 30 months after the contamination, affecting the top 10 cm layer.
- A₈: *Treatment of contaminated fish and Bans on fish consumption* There are several kinds of treatments, such as removing the bones or salting the fish. The first is quite effective for reducing Sr⁹⁰ intake, whereas fish salting can reduce Cs¹³⁷ by 70%.

The above countermeasures were also compared with A₉: *No action*, i.e., the natural evolution of the situation without intervention. Further information about the countermeasures under consideration can be found in Gallego and Magán (2009).

Table 2 shows the impacts or performances for the different attributes with a continuous scale for the nine countermeasures under consideration. These impacts were gathered from MOIRA system, which includes a complete set of reliable, validated models (Monte et al. 2009) to predict the long-term temporal behavior of radionuclides in the freshwater environment and the ecological, social and economic impacts of the intervention countermeasures.

Note that although the table includes precise impacts, percentage deviations were used to account for uncertainty about some such impacts. Specifically, a 20% deviation was introduced in X₁ and X₈, a 10% for X₅ and X₇; and deviations ranging from –10 to +30% were used to derive the least and most impact for attributes X₃ and X₄, respectively.

Besides, DM preferences were modeled by an additive multi-attribute utility function, whose functional form is

$$u(A_i) = \sum_{j=1}^n w_j u_j(x_{ij}),$$

where x_{ij} is the impact of countermeasure A_i with respect to attribute X_j , $u_j(\cdot)$ is the component utility function representing DM preferences for the impacts of attribute X_j and w_j is the weight representing the relative importance of each attribute. Note that $\sum_j w_j = 1$ and $w_j \geq 0$.

Imprecision was considered regarding the DMs' preferences when assessing both the DMs' component utilities, $u_j(\cdot)$, and weights. In the first case, classes of component utility functions were derived from the elicitation methods (Jiménez et al. 2003) and, consequently, the component utility associated with a specific impact would belong to an interval. Alternatively, ordinal information about the component utilities of the countermeasures was considered (Sarabando and Dias 2010; Aguayo et al. 2014), i.e., the DM provided a ranking of the countermeasures for some attributes. Moreover, rankings of the difference between the values of consecutive countermeasures was also taken into account for some attributes.

Besides, imprecision on weights representing the relative importance of criteria was represented by means of ordinal information.

Three experts participated in the ecosystem restoration problem solving: D. Cancio, former Head of the Public and Environmental Radiological Protection Unit (CIEMAT, *Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas—Energy, Environment and Technology Research Centre*); P. Carboneras, former Director of the Safety and Licensing Department at ENRESA (*Empresa Nacional de Residuos Radiactivos S.A.—National Radioactive Waste Management Company*), and E. Gallego, Professor of Nuclear Engineering at the UPM and public and environmental radiological protection expert. Another expert assuming a more ecological role (DM_4) was also involved in the analysis.

The relative importance of the experts was as follows: the ecology expert was assigned a weight of 0.1, whereas the other three experts were considered equally important as each other and each was assigned a weight of 0.3.

Figure 2 shows the utility functions for X_1 : Lake Ecosystem Index and X_3 : Dose to Critical Individuals. An imprecise piecewise utility function was considered for X_3 , whereas a precise nonlinear decreasing utility function was used for X_1 (Håkanson et al. 2000). For the remaining attributes, a precise linear decreasing utility function was considered in the corresponding attribute range.

Fig. 2 Component utility functions for X_1 and X_3

Table 3 Ordinal information concerning countermeasures

	Ordinal information
X_2 : Dose to Fish	$A_7 > \{A_2, A_3, A_4, A_5, A_6, A_8, A_9\} > A_1$
X_9 : Cost to Image	
DM_1	$\{A_1, A_2, A_3, A_4, A_5, A_6\} > A_8 > A_7$
DM_2	$A_7 > \{A_1, A_2, A_3, A_4, A_5, A_6\} > A_8 > A_9$
DM_3	$A_7 > \{A_2, A_5\} > \{A_1, A_3, A_4, A_6\} > A_8 > A_9$
DM_4	$\{A_6, A_7, A_8\} > \{A_3, A_4\} > \{A_1, A_2, A_5\} > A_9$

Table 4 Ordinal information about the difference between the countermeasures

	Ordinal information
X_2 : Dose to Fish	$\Delta_{2\{7,2\}} > \Delta_{2\{9,1\}}$
X_9 : Cost to Image	
DM_1	$\Delta_{9\{8,7\}} > \Delta_{9\{6,8\}}$
DM_2	$\Delta_{9\{7,1\}} > \Delta_{9\{8,9\}} > \Delta_{9\{6,8\}}$
DM_3	$\Delta_{9\{7,2\}} > \Delta_{9\{8,9\}} > \{\Delta_{9\{5,1\}}, \Delta_{9\{6,8\}}\}$

Table 3 shows the ordinal information concerning the appraisal of the nine countermeasures in X_2 : Dose to Fish and X_9 : Cost to Image. Note that as X_9 : Cost to Image is subjective, ordinal information for each DM was incorporated to the analysis, whereas the ordinal information concerning the appraisal of X_2 : Dose to Fish was not subjective and ordinal information accounting for all the DMs was considered. Note also that countermeasures in braces were equally valued.

Moreover, rankings of the difference between the values of some consecutive countermeasures were also taken into account by DMs for some attributes, see Table 4.

For X_2 : Dose to Fish, we have $A_7 > \{A_2, A_3, A_4, A_5, A_6, A_8, A_9\} > A_1$ and $\Delta_{2\{7,2\}} > \Delta_{2\{9,1\}}$, where

$$\begin{aligned}
 \Delta_{2\{7,2\}} &= v_2(A_7) - v_2(A_2), & \Delta_{2\{2,3\}} &= v_2(A_2) - v_2(A_3) = 0, \\
 \Delta_{2\{3,4\}} &= v_2(A_3) - v_2(A_4) = 0, & \Delta_{2\{4,5\}} &= v_2(A_4) - v_2(A_5) = 0, \\
 \Delta_{2\{5,6\}} &= v_2(A_5) - v_2(A_6) = 0, & \Delta_{2\{6,8\}} &= v_2(A_6) - v_2(A_8) = 0, \\
 \Delta_{2\{8,9\}} &= v_2(A_8) - v_2(A_9) = 0, & \Delta_{2\{9,1\}} &= v_2(A_9) - v_2(A_1).
 \end{aligned}$$

This means that the difference in the appraisal of countermeasure A_7 regarding $\{A_2, A_3, A_4, A_5, A_6, A_8, A_9\}$ is greater than the difference in the appraisal of that set regarding A_1 .

For X_9 : Cost to Image, we have for DM_3 $A_7 > \{A_2, A_5\} > \{A_1, A_3, A_4, A_6\} > A_8 > A_9$ and $\Delta_{9\{7,2\}} > \Delta_{9\{8,9\}} > \{\Delta_{9\{5,1\}}, \Delta_{9\{6,8\}}\}$, where

$$\begin{aligned}
 \Delta_{9\{7,2\}} &= v_9(A_7) - v_9(A_2), & \Delta_{9\{2,5\}} &= v_9(A_2) - v_9(A_5) = 0, \\
 \Delta_{9\{5,1\}} &= v_9(A_5) - v_9(A_1), & \Delta_{9\{1,3\}} &= v_9(A_1) - v_9(A_3) = 0,
 \end{aligned}$$

Table 5 Ordinal information concerning weights

	Ordinal information
DM_1	$w_3^1 > w_8^1 > w_9^1 > w_4^1 > \{w_5^1, w_6^1\} > w_7^1 > w_2^1 > w_1^1$
DM_2	$w_3^2 > w_4^2 > w_9^2 > w_6^2 > w_8^2 > w_7^2 > w_1^2 > w_2^2 > w_5^2$
DM_3	$\{w_3^3, w_4^3\} > w_8^3 > w_6^3 > w_9^3 > w_7^3 > \{w_1^3, w_2^3, w_5^3\}$
DM_4	$\{w_1^4, w_2^4\} > \{w_3^4, w_4^4\} > \{w_5^4, w_6^4\} > \{w_7^4, w_8^4\} > w_9^4$

Table 6 Ordinal information about the difference between the weights

DM	Ordinal information
DM_1	$\Delta_{1\{3,8\}} > \Delta_{1\{9,4\}} > \{\Delta_{1\{6,7\}}, \Delta_{1\{7,2\}}\} > \{\Delta_{1\{8,9\}}, \Delta_{1\{4,5\}}, \Delta_{1\{2,1\}}\}$
DM_2	$\Delta_{2\{1,2\}} > \Delta_{2\{2,5\}} > \Delta_{2\{4,9\}} > \{\Delta_{2\{3,4\}}, \Delta_{2\{9,6\}}, \Delta_{2\{6,8\}}, \Delta_{2\{8,7\}}, \Delta_{2\{7,1\}}\}$
DM_3	$\Delta_{3\{4,8\}} > \Delta_{3\{8,6\}} > \Delta_{3\{6,9\}} > \Delta_{3\{9,7\}} > \Delta_{3\{7,1\}}$

$$\begin{aligned}\Delta_{9\{3,4\}} &= v_9(A_3) - v_9(A_4) = 0, & \Delta_{9\{4,6\}} &= v_9(A_4) - v_9(A_6) = 0, \\ \Delta_{9\{6,8\}} &= v_9(A_6) - v_9(A_8), & \Delta_{9\{8,9\}} &= v_9(A_8) - v_9(A_9).\end{aligned}$$

In this case, the difference in the appraisal of countermeasure A_7 regarding $\{A_2, A_5\}$ is greater than the difference in the appraisal of countermeasures A_9 and A_8 , which is greater than the other two differences in appraisal.

Each DM also used ordinal information to represent imprecision with respect to weights in the restoration problem under consideration, as shown in Table 5.

Rankings of the difference between the values of some consecutive weights were also taken into account by some DMs, see Table 6.

4 Veto in MCDM

The concept of veto was originally justified in social theory by the *prudence axiom* enunciated by Arrow and Raynaud (1986). The main idea behind this axiom is that it is not prudent to accept highly conflicting alternatives that may result in vulnerable decisions. Regarding the prudence axiom, Moulin defines the *principle of proportional veto* within a group of DMs (Moulin 1981), according to which any coalition of DMs should be given the right to veto a certain number of alternatives, which is approximately proportional to the size of this coalition. In addition, the allocation of veto power across the various groups of social participants has ethical implications, since it entails attaching different weights to different groups.

In MCDM problems the concept of veto has been used to manage *non-compensatory methods*. In outranking methods the use of veto usually represents the intensity of preference of the minority (Roy and Slowinski 2008). For instance, Nowak (2004) used *ELECTRE-III* to build a multi-attribute ranking using preference thresholds to distinguish situations of strict and weak preference in stochastic dominance approaches.

Later, Munda (2009) implemented a veto-based threshold to deal with environmental and resource management and policies aimed at sustainable development. A fuzzy set theory framework was used to represent *qualitative information* by means of the concept of *linguistic variable*. Ranking policy options were derived by means of the majority principle implemented by Concordet, whereas the power of a subgroup of DMs to veto some alternatives was accounted for by means of Moulin's proportional veto function.

More recently, Greco et al. (2011) proposed a new method, called *ELECTRE^{GKMS}*. *ELECTRE^{GKMS}* employs robust ordinal regression to construct a set of outranking models compatible with preference information. It builds a set of values of concordance indices, concordance thresholds, indifference, preference, and veto thresholds, for which all specified pairwise comparisons can be restored.

On the other hand, additive *compensatory methods* have also incorporated the concept of veto. For instance, Bana e Costa et al. (2002) define a multi-criteria approach for prohibiting alternatives by the *measuring attractiveness by a categorical based evaluation technique* (MACBETH) for facilitating bid evaluation processes, such as interventions in an international public call for tenders. The result is a procedure called the *determinants technique*, whose groundwork is aligned, albeit not directly, with the notion of *veto power* used to model non-compensatory situations.

In connection with research based on the power of veto, Marichal (2004) proposes axiomatizing individual indices to rate whether each criterion behaves as a veto or an aggregator using the Choquet integral. These indices for measuring the degree to which each criterion behaves like a blocker or a pusher make it possible to identify and measure the *dictatorial* tendency of criteria, which is a particular interaction phenomenon. Here, the veto is not a preference parameter given by the DM but an effect phenomenon when aggregating criteria. Therefore, the veto concept is related to the impact caused by a criterion on the global evaluation of alternatives.

Liginlala and Ow (2006) use the same idea of veto effects, expressing degrees of conjunction, disjunction, veto and approval given by the indices through fuzzy analysis measures, which represent a risk tolerance measure of the DM. The veto power examines how tolerant DMs are about accepting or rejecting evaluations of alternatives associated with specific actions on a given attribute.

Daher and de Almeida (2012) developed an additive group preference model that incorporates a utility reduction factor. DMs express their preferences in terms of a ranking of alternatives and are able to make an informed veto by providing information about the undesirable or unacceptable ranking of some alternatives. The ranking veto is achieved by using a reduction factor on the global utility of the alternatives.

More recently, de Almeida (2013) proposed two additive-veto models for choice and ranking problems, respectively. The level of veto is represented by two thresholds. This introduces some vagueness in the DM's specification of this level.

Then, if a choice problem is considered, veto functions of all attributes are aggregated by the product function and incorporated into the additive model and the global value/utility is set to 0 if the performance of the alternative is unacceptable for any of the attributes. In ranking problems, the veto function rejects the position of the vetoed alternative in the ranking process rather than the alternative itself. Weight veto functions are aggregated by summation and incorporated into the additive model.

In this paper, as in de Almeida (2013), we propose an additive-veto model for ranking problems, albeit in a group decision-making context. Veto values provided by DMs are precise and expressed in terms of alternative performances. Then, veto values for the most important DMs are used to define veto ranges, whereas veto values corresponding to the other less important DMs are partially taken into account, leading to the construction of adjust ranges.

Approaches by Daher and de Almeida (2012) and de Almeida (2013) are described in more detail and compared with the use of veto values in the group decision-making context with partial information as proposed in this paper in Sect. 6.

4.1 Accounting for Veto Values in a Group Decision-Making Context

We now extend the decision-making framework with the incomplete information to a group decision-making context in which DMs are allowed to provide vetoes for the alternative performances with respect to the attributes under consideration.

Then, we consider a set of k DMs, denoted by DM_l , $l = 1, \dots, k$, whose relative importance is known and denoted by w_{DM_l} . Without loss of generality, we assume that the most important DM is DM_1 , followed by DM_2 , and so on up to DM_k . Consequently, $w_{DM_1} \geq w_{DM_2} \geq \dots \geq w_{DM_k}$, and $\sum_l w_{DM_l} = 1$.

The question of how to measure the weights of DMs in a group decision-making context is an interesting research topic. Yue (2011) provides a brief overview of approaches proposed by different authors to determine the weights of DMs. Besides, a new approach based on an extended TOPSIS method (Yoon 1980; Hwang and Yoon 1981) is also proposed.

We assume that weight intervals or ordinal information about weights are available for each DM, $\mathbf{w}^l = (w_1^l, \dots, w_n^l) \in W^l$, $l = 1, \dots, k$, representing the relative importance of their attributes. Moreover, imprecise component utility functions have been built or ordinal information about the utility of the alternatives has been provided by the DMs for the attributes under consideration, U_j^l , $l = 1, \dots, k$ and $j = 1, \dots, n$.

All DMs are allowed to provide veto values, but the corresponding veto will be effective for only the r most important DMs, $r \leq k$. Veto values corresponding to the $k - r$ remaining DMs will be partially taken into account, as described later.

We denote by v_j^l the veto threshold provided by the l -th DM for the attribute X_j , i.e. the l -th DM wants the alternative performances to be greater (less) than v_j^l if an increasing (decreasing) component utility function is associated with attribute X_j . Consequently, the veto interval for the l -th DM is $(0, v_j^l]$ in attribute X_j . For simplicity's sake, we will consider from now on that component utility functions are increasing.

A *veto range* can then be identified for each attribute $[v_j^L, v_j^U]$, where $v_j^L = r_j^L$, $[r_j^L, r_j^U]$ being the attribute range, and $v_j^U = \max_{l=1, \dots, r} \{v_j^l\}$, i.e., the highest veto value for attribute X_j for the r most important DMs.

We build an *adjust range* for each attribute X_j , $(a_j^L, a_j^U]$, with $a_j^L = v_j^U$, and $a_j^U = \max_{l=1, \dots, k} \{v_j^l\}$, i.e., the highest veto value for attribute X_j considering all DMs.

Fig. 3 Adjust function

We add the above information to the additive multi-attribute utility function by means of the following functions (assuming increasing component utility functions):

- $v(A_i)$ is the *veto function* that checks if the performances for a given A_i are within the respective veto intervals:

$$v(A_i) = \prod_{j=1}^n v_j(A_i), \quad \text{with } v_j(A_i) = \begin{cases} 1, & \text{if } x_{ij} > v_j^U \\ 0, & \text{if } x_{ij} \leq v_j^U \end{cases}$$

Note that $v(A_i) = 0$ if at least one performance is within the veto interval for the corresponding attribute.

- $d_j(A_i)$ is the *adjust function* that decreases the utility associated with the alternative performances within the corresponding adjust range. A first possible approach is to apply a linear adjust function. However, we believe that the veto values for the $k - r$ less important DMs should be added by means of this adjust function. Veto values provided by the $k - r$ DMs may be within the adjust interval. In this case, we use this information to build a piecewise linear function.

For example, let us assume that the adjust range is $[20, 50]$, 50 being the highest veto value provided by the DMs. Then, if two of the $k - r$ less important DMs have provided the veto values 23 and 35, i.e. veto values within the adjust range, then the corresponding adjust function is as shown in Fig. 3. Note that the adjust values for the considered vetoes are 0.33 and 0.66, respectively. In case of three veto values within the adjust range, their adjust values would be 0.25, 0.5 and 0.75.

Table 7 shows the veto values provided by the DMs for the restoration problem under consideration. Note that, DMs do not provide veto values for all attributes, and the only veto for attribute X_6 is provided by DM_1 . Besides, as component utility functions are decreasing for all three attributes, the vetoed values are the values greater than the veto values provided by DMs. Note that the respective veto will be effective for the three most important DMs only, i.e., DM_1 , DM_2 and DM_3 .

The veto intervals for X_1 , X_3 and X_6 are $[1.7, 5]$, $[100, 500]$ and $[24, 360]$, respectively; whereas adjust intervals are $[1.6, 1.7]$ and $[90, 100]$, corresponding to attributes X_1 and X_3 , i.e., no adjust interval is identified for X_6 . Thus, countermeasure A_6 : *Fertilization* is vetoed since its impact interval for X_1 is $[1.766, 2.354]$ within the veto

Table 7 Veto values for DMs

DM	X_1 (LEI)	X_3 (mSv)	X_6 (months)
DM_1	–	100	24
DM_2	1.7	100	–
DM_3	2	–	–
DM_4	1.6	90	–

Fig. 4 Adjust functions for X_1 and X_3

interval $[1.7, 5]$. A_8 : *Treatment of contaminated fish and Bans on fish consumption* is also vetoed since its impact on X_6 is 36, which falls within the veto interval $[24, 360]$. Consequently, neither countermeasure will be considered for further analysis.

The adjust functions for attributes X_1 and X_3 are shown in Fig. 4. The upper endpoint of the performance interval for countermeasure A_1 : *Single Potassium addition* with respect to X_1 , 1.609, is within the corresponding adjust interval. Thus, the original component utility, 0.4, is reduced according to the adjust function leading to $0.4 \times 0.91 = 0.364$. The same applies to A_3 : *Lake liming*, whose reduced lower component utility in A_1 is $0.41 \times 0.88 = 0.3608$. Note that the adjust functions have little effect on the evaluation of alternatives in the problem under consideration, but this might not be the case in other decision-making contexts.

5 Group Decision-Making Within MAUT with Incomplete Information Accounting for Veto

The adaptation of the additive multi-attribute utility function to account for the veto and adjust functions is as follows:

$$u^l(A_i) = \left[\sum_{j=1}^n u_j^l(x_{ij}) w_j^l d_j(A_i) \right] \times v(A_i), \quad (1)$$

with

$$\mathbf{w}^l \in W^l = \left\{ (w_1^l, \dots, w_n^l) \mid w_{(1)}^l \geq w_{(2)}^l \geq \dots \geq w_{(n)}^l \geq 0 \right\},$$

i.e. ordinal information regarding the relative importance of criteria ($\sum_{j=1}^n w_i = 1$) and $d_j(A_i)$ and $v(A_i)$ are the adjust and veto functions, respectively, as described in Sect. 4.1.

Regarding component utilities, classes of component utility functions could be derived from the elicitation methods (Jiménez et al. 2003). This applies to the attributes in Table 2. Then,

$$\mathbf{u}_j \in U_j = \left\{ (u_j(x_{1j}), \dots, u_j(x_{mj})) \mid u_j^L(x_{ij}^L) \leq u_j(x_{ij}) \leq u_j^U(x_{ij}^U), \quad i = 1, \dots, m \right\},$$

or

$$\mathbf{u}_j \in U_j = \left\{ (u_j(x_{1j}), \dots, u_j(x_{mj})) \mid u_j^L(x_{ij}^U) \leq u_j(x_{ij}) \leq u_j^U(x_{ij}^L), \quad i = 1, \dots, m \right\},$$

for an increasing or decreasing utility function, respectively.

Alternatively, ordinal information about the component utilities of the alternatives could be provided by the DMs (Sarabando and Dias 2010; Aguayo et al. 2014). This applies to X_2 : Dose to Fish and X_9 : Cost to Image, see Table 3. Then,

$$\mathbf{u}_j^l \in U_j^l = \left\{ (u_j(x_{1j})^l, \dots, u_j(x_{mj})^l) \mid u_j(x_{(1)j})^l \geq u_j(x_{(2)j})^l \geq \dots \geq u_j(x_{(m)j})^l \right\}.$$

Moreover, rankings of the difference between the values of consecutive alternatives has been provided for both attributes, see Table 4.

Note that although the above expression considers the preferences concerning weights and some component utilities regarding the l -th DM, the resulting utility is influenced by the opinion of the other DMs by means of the veto and adjust functions.

We now propose a methodology accounting for this specific group decision-making problem to derive a group ranking. The methodology consists of two aggregation phases. In the first phase, a *dominance measuring method* is used to exploit the uncertainty about the countermeasure impacts and imprecise information concerning DM preferences to derive a ranking of alternatives for each DM. In the second phase, the different rankings derived in the first phase are aggregated taking into account the relative importance of DMs to reach a group ranking using the order explicit algorithm method, an extension of Kemeny optimal aggregation.

5.1 A Dominance Measuring Method for Deriving Alternative Rankings

Dominance measuring methods (DMMs) are based on the computation of a *dominance matrix*, D , including pairwise dominance values. Dominance matrix for the l -th DM, D^l , can be defined as follows:

$$D^l = \begin{pmatrix} - & D_{12}^l & \cdots & D_{1(m-1)}^l & D_{1m}^l \\ D_{21}^l & - & \cdots & D_{2(m-1)}^l & D_{2m}^l \\ D_{31}^l & D_{32}^l & \cdots & D_{3(m-1)}^l & D_{3m}^l \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ D_{m1}^l & D_{m2}^l & \cdots & D_{m(m-1)}^l & - \end{pmatrix},$$

where

$$\begin{aligned} D_{ks}^l &= \min\{u^l(A_k) - u^l(A_s)\} \\ \text{s.t.} \quad & u_j(x_{kj}), u_j(x_{sj}) \in U_j, \quad j = 1, 3, 4, 5, 6, 7, 8 \\ & u_j^l(x_{kj}), u_j^l(x_{sj}) \in U_j^l, \quad j = 2, 9, \\ & \mathbf{w}^l = (w_1^l, \dots, w_n^l) \in W^l, \end{aligned}$$

with

$$u^l(A_i) = \left[\sum_{j=1}^n u_j^l(x_{ij}) w_j^l d_j(A_i) \right] \times v(A_i).$$

Note that given two alternatives A_k and A_s , alternative A_k dominates A_s if $D_{ks}^l \geq 0$, and there exists at least one combination of values for the imprecise weights and component utilities under consideration such that the overall value of A_k is strictly greater than that of A_s . This concept of dominance is called *pairwise dominance*. We have to solve quadratic optimization problems in order to compute pairwise dominance values.

Different *DMMs* can be found in the literature (Ahn and Park 2008; Jiménez et al. 2013; Aguayo et al. 2014; Mateos et al. 2014; Aguayo 2014). They differ as to how they exploit the information included in the dominance matrix to derive the ranking of alternatives. Their performance has been compared with other approaches to deal with incomplete information, such as the modification of four classical decision rules to encompass an imprecise decision context (Puerto et al. 2000; Salo and Hämäläinen 2001), *surrogate weighting methods* (Barron and Barret 1996; Stillwell et al. 1981), the *stochastic multicriteria acceptability analysis (SMAA)* method (Lahdelma et al. 1998) and its extensions, *SMAA-2* (Lahdelma and Salminen 2001) and *SMAA-O* (Lahdelma et al. 2003); or Sarabando and Dias' method (2009).

Most recent *DMMs* outperform most of the approaches under comparison. Besides, approaches for which there was no significant difference regarding *DMMs*, *ROC* (a surrogate weighting method), *SMAA-2* and Sarabando and Dias' method, have the drawback of only being applicable for specific ways of representing the imprecise information about the DMs' preferences, whereas *DMMs* can incorporate and combine different ways of representing such imprecision, as illustrated in the example introduced in Sect. 4.

The *DMM* that we use Aguayo (2014) derives a *global dominance intensity index* to rank alternatives on the basis that

$$D_{ks}^l \leq u^l(A_k) - u^l(A_s) \leq |D_{sk}^l|.$$

First, the pairwise dominance values in D^l are weighted according to the distance between the central weight vector (w_j^{lc}) and the weight vector (w_j^{l*}) associated with the optimal D_{ks}^l , when solving the corresponding optimization problem, i.e.,

$$\bar{D}_{ks}^l = \frac{D_{ks}^l}{d(w_j^{lc}, w_j^{l*})}.$$

The aim is to attach more importance to weight vectors closer to the central weight vector.

Then, we perform the following algorithm:

1. If $\bar{D}_{ks}^l \geq 0$, then alternative A_k dominates A_s , and the dominance intensity of A_k over A_s is $DI_{ks}^l = d([\bar{D}_{ks}^l, -\bar{D}_{sk}^l], 0)$.

Else ($\bar{D}_{ks}^l < 0$):

- If $\bar{D}_{sk}^l \geq 0$, then A_s dominates A_k , and $DI_{ks}^l = -d([\bar{D}_{ks}^l, -\bar{D}_{sk}^l], 0)$.
- Else ($\bar{D}_{sk}^l < 0$),

$$DI_{ks}^l = \left[\frac{-\bar{D}_{sk}^l}{-\bar{D}_{sk}^l - \bar{D}_{ks}^l} - \frac{-\bar{D}_{ks}^l}{-\bar{D}_{sk}^l - \bar{D}_{ks}^l} \right] \times d([\bar{D}_{ks}^l, -\bar{D}_{sk}^l], 0).$$

2. Calculate a global dominance intensity (GDI^l) for each alternative A_k , i.e., $GDI_k^l = \sum_{s=1, s \neq k}^m DI_{ks}^l$, and rank the alternatives according to them.

Note that the method incorporates the distance from the intervals $[\bar{D}_{ks}^l, -\bar{D}_{sk}^l]$ to 0 to account for their sizes and how far they are from 0. The distance d used was proposed in Mateos et al. (2007), which takes into account every point in the interval.

For the restoration problem under consideration, the corresponding quadratic optimization problems were solved to compute pairwise dominance values and derive the following *dominance matrices* for the four DMs under consideration:

$$D^1 = \begin{pmatrix} - & -0.1569 & -0.1746 & -0.1362 & -0.1042 & -0.1466 & -0.1272 \\ -0.1956 & - & -0.2363 & -0.2169 & -0.1866 & -0.2189 & -0.2607 \\ -0.1924 & -0.1806 & - & -0.2257 & -0.1179 & -0.0966 & -0.1823 \\ -0.2105 & -0.2034 & -0.1794 & - & -0.1949 & -0.1832 & -0.2814 \\ -0.2203 & -0.1662 & -0.1669 & -0.1895 & - & -0.1793 & -0.1953 \\ -0.2000 & -0.1484 & -0.1539 & -0.1570 & -0.0876 & - & -0.1591 \\ -0.1762 & -0.0972 & -0.1589 & -0.1914 & -0.1214 & -0.1139 & - \end{pmatrix},$$

Table 8 Global dominance intensities and countermeasure rankings for DMs

	DM_1	DM_2	DM_3	DM_4	Group
1st	$A_9(0.1162)$	$A_1(0.2398)$	$A_1(0.1904)$	$A_1(0.2932)$	A_1
2nd	$A_1(0.1094)$	$A_7(0.1506)$	$A_3(0.1453)$	$A_3(0.1427)$	A_9
3rd	$A_3(0.0235)$	$A_9(0.0278)$	$A_9(0.1419)$	$A_2(0.0163)$	A_3
4th	$A_7(0.0125)$	$A_3(-0.0051)$	$A_7(0.0305)$	$A_9(-0.0494)$	A_7
5th	$A_4(-0.0419)$	$A_4(-0.1158)$	$A_4(-0.0492)$	$A_7(-0.0843)$	A_4
6th	$A_5(-0.1006)$	$A_2(-0.1362)$	$A_2(-0.1811)$	$A_5(-0.1022)$	A_2
7th	$A_2(-0.1193)$	$A_5(-0.1611)$	$A_5(-0.2778)$	$A_4(-0.2164)$	A_5

$$D^2 = \begin{pmatrix} - & -0.1572 & -0.1553 & -0.2035 & -0.0298 & -0.1567 & -0.1713 \\ -0.3054 & - & -0.2034 & -0.2985 & -0.2120 & -0.3098 & -0.3407 \\ -0.2348 & -0.1991 & - & -0.1825 & -0.2397 & -0.3225 & -0.2338 \\ -0.2648 & -0.3035 & -0.2591 & - & -0.2763 & -0.3061 & -0.2371 \\ -0.3146 & -0.1970 & -0.3190 & -0.1922 & - & -0.2523 & -0.1846 \\ -0.1705 & -0.1095 & -0.2250 & -0.1849 & -0.1967 & - & -0.2134 \\ -0.2107 & -0.3127 & -0.2365 & -0.2039 & -0.1255 & -0.1981 & - \end{pmatrix},$$

$$D^3 = \begin{pmatrix} - & -0.1174 & -0.1475 & -0.2228 & -0.06158 & -0.1918 & -0.1567 \\ -0.3291 & - & -0.2416 & -0.1875 & -0.2513 & -0.2255 & -0.3403 \\ -0.2314 & -0.0780 & - & -0.1416 & -0.1506 & -0.1905 & -0.1855 \\ -0.1979 & -0.2553 & -0.2857 & - & -0.1075 & -0.3162 & -0.2131 \\ -0.2425 & -0.2714 & -0.2851 & -0.3056 & - & -0.2456 & -0.2689 \\ -0.2255 & -0.1777 & -0.2300 & -0.1620 & -0.1776 & - & -0.2113 \\ -0.1836 & -0.1836 & -0.2005 & -0.1743 & -0.1071 & -0.1094 & - \end{pmatrix},$$

$$D^4 = \begin{pmatrix} - & 0.0897 & -0.0707 & -0.0923 & 0.0078 & -0.0006 & -0.0099 \\ -0.1349 & - & -0.0302 & -0.0995 & -0.1138 & -0.0257 & -0.1489 \\ -0.1206 & -0.0193 & - & -0.0456 & 0.0249 & -0.0461 & -0.1712 \\ -0.0770 & -0.2456 & -0.1263 & - & -0.1095 & -0.2414 & -0.0706 \\ -0.0511 & -0.1594 & -0.1666 & -0.0631 & - & -0.0197 & -0.1137 \\ -0.0671 & -0.2201 & -0.1444 & 0.0183 & -0.0958 & - & -0.0525 \\ -0.1946 & -0.0665 & -0.1154 & -0.1351 & -0.1117 & -0.0043 & - \end{pmatrix}.$$

Table 8 shows the global dominance intensities (GDIs) associated with each countermeasure and the resulting rankings for the DMs under consideration. Note that it would be wrong to refer to such rankings as individual rankings or as the ranking representing the preferences of the l -th DM, as the resulting utilities are influenced by the opinion of other DMs in the extension of the additive multi-attribute utility model to account for veto values.

5.2 Aggregating Alternative Rankings

In the second phase of the proposed methodology, the k rankings output in the first phase have to be aggregated. As mentioned in the introduction, different meth-

ods for aggregating rankings by different authors can be found in the literature (Lin 2010).

In our decision-making scenario, complete rankings and the relative importance of such rankings (relative importance of DMs) are available. Moreover, the values that lead to the corresponding rankings (global dominance intensities) derived from the dominance measuring method are also available. The only aggregation method to exploit all the above information is the Kemeny method (1959) and its extensions.

Kemeny optimal aggregation optimizes the average Kendall distances between a candidate aggregate ranking and each of the input rankings. As computing the Kemeny optimal aggregate is NP-hard even when the number of ranked lists to be aggregated is small, we have used the *order explicit algorithm* (OEA) Lin and Ding (2009) to solve the combinatorial problem under consideration.

OEA uses a global optimization technique, called the *cross-entropy Monte Carlo method*, which searches iteratively for an optimal list that minimizes a criterion, the sum of weighted distances between the candidate (aggregate) list and each of the input ranked lists. The method is, however, general and amenable to any other optimization criterion. A modified Kendall's tau measure and *Spearman's footrule* are used to measure the distance between two ranked lists.

The OEA algorithm has been implemented using R. The program and documentation are available at <http://www.stat.osu.edu/?statgen/TopKCEMC>. RankAggreg Pihur et al. (2009) is another R package for weighted rank aggregation including OEA, <https://cran.r-project.org/web/packages/RankAggreg/RankAggreg.pdf>.

The last column of Table 8 shows the resulting group ranking, in which the relative importance of DMs has been taken into account. Note that alternative A_1 : *Potassium addition* (single treatment) is best ranked in the group ranking, followed by A_9 : *No action* and A_3 : *Lake liming*. Alternative A_1 was best ranked by all DMs but DM_1 , who placed it second.

6 Comparative Analysis

As cited in Sect. 4, de Almeida (2013) proposed two additive-veto models for choice and ranking problems, respectively, in which some vagueness was introduced in the DM's specification of veto values by two thresholds. In fact, the DM is willing to accept an alternative whose value/utility is above the upper threshold, the DM rejects alternatives with value/utility below the lower threshold, and a linear veto function between 0 and 1 is used to reduce the global value/utility of the alternative otherwise.

In ranking problems, the veto function rejects the position of the vetoed alternative in the ranking process rather than the alternative itself. The weighted veto functions of all attributes are aggregated by summation and incorporated into the additive model and the global value/utility is set to 0 if the performance of the alternative is unacceptable for all attributes. Otherwise, the global value/utility of an alternative vetoed in some attributes is reduced.

In contrast with the additive-veto model proposed in de Almeida (2013), veto values provided by DMs in this paper are precise and expressed in terms of alternative performances rather than alternative utilities, which DMs find easier to do, as they

suggested at meetings held. Moreover, alternatives whose performances are unacceptable (vetoed) for any of the attributes are rejected in our approach irrespective of the value that they take for other attributes. DMs highlighted this issue.

Moreover, the model in de Almeida (2013) is not applied in a group decision-making context by contrast with our approach, where all DMs are allowed to provide veto values, but the corresponding veto is effective for only the most important DMs, whereas veto values corresponding to the remaining DMs are partially taken into account by means of the adjust function.

To conclude, the two approaches cannot be compared with respect to the restoration problem under consideration mainly because the proposal in de Almeida (2013) does not account for a group decision-making context.

On the other hand, the proposal by Daher and de Almeida (2012) accounts for a group decision-making context. It was developed to mitigate the compensatory effects of additive aggregation in group decision-making by introducing ranking vetoes based on a reduction factor to penalize conflicting alternatives and reduce disagreements. Specifically, Daher and de Almeida's proposal is based on three concepts: *veto thresholds*, the *virtual alternative* and the *utility reduction factor (URF)*.

Veto threshold, α_l , represents the minimum acceptable utility value for DM_l , i.e. any alternative for which the individual utility value is less than α_l is considered as unacceptable or undesirable for that DM and potentially conflicting.

Alternative A_α is a virtual alternative consisting of all individual utility values in $\alpha = (\alpha_1, \dots, \alpha_k)$. The aggregation of all individual utility values of α defines the global utility of a virtual alternative, $u(A_\alpha)$. When a vector representation is used, the virtual alternative affords four different sub-areas, created by the intersection of threshold values: a *positive concordance zone* where all DMs are willing to accept alternatives placed in that region; a *negative concordance zone* where all DMs are willing to reject alternatives placed in that region; and *discordance zones* where at least one DM considers an alternative placed in that region as unacceptable or undesirable as a group solution.

Finally, the *URF* is used to penalize any alternative located in discordance zones, as follows:

$$u(A_i) = URF \times \sum_{l=1}^k w_{DM_l} u^l(A_i), \quad (2)$$

where $URF = 1$, if the alternative belongs to a concordance zone (positive or negative), or $URF = u(A_\alpha)$, if an alternative belongs to a discordance zone and has an original utility value higher than the virtual alternative utility value.

The utility value of potentially conflicting alternatives is reduced to the same value as the virtual alternative, and, consequently, they have the same rank position. Different *URF* rules such as a linear or geometric *URF* could be considered.

Note that the approach by Daher and de Almeida does not consider decision-making with partial or imprecise information and the group ranking is derived from an additive form that accounts for the relative importance of DMs, see Eq. (2). However, we account for uncertainty about the alternative performances and imprecision concerning DM preferences, which is exploited together with veto values in a dominance

measuring method to derive rankings of alternatives, which are then aggregated using the OEA algorithm.

Daher and de Almeida's approach cannot be adapted to the group decision-making context since veto thresholds represent the minimum acceptable utility value for DMs, whereas our rankings are built on the basis of global dominance intensities.

7 Conclusions

In this paper we have dealt with a real group decision-making problem centered on the restoration of a radionuclides contaminated lake. We have extended the additive multiattribute utility model to incorporate the concept of veto in this group decision-making context. Additionally, we have considered uncertainty about the alternative performances and imprecision concerning DMs' preferences, which can be represented by intervals or ordinal information.

We have proposed a methodology consisting of two aggregation phases. In the first phase, the additive multi-attribute utility model is adapted to account for DM vetoes. Veto values for the most important DMs are used to define veto ranges, whereas veto values corresponding to the other less important DMs are partially taken into account, leading to the construction of adjust ranges. Then, a dominance measuring method, a recent approach for dealing with incomplete information based on the pairwise dominance notion is used to derive a ranking of alternatives for each DM.

In the second phase, the different rankings derived in the first phase are aggregated taking into account the relative importance of DMs to reach a group ranking using the *order explicit algorithm method*, an extension of Kemeny optimal aggregation.

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