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Reference-based ranking procedure for environmental decision making: Insights from an ex-post analysis

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ABSTRACT

Preference elicitation is a challenging activity in any decision-making process, yet preferences are fundamental since the recommendations are meaningful and acceptable only if the Decision Maker's values are taken into account. This study proposes an ex-post application of a recent ranking method named Simple Ranking with Multiple Points (S-RMP) to support a participatory decision-making process. The method has been tested on a real-world case study simulating the selection of the most suitable site for locating a new landfill. The purpose of the research is twofold: (i) to explore the applicability and relevance of the S-RMP method to support environmental decision-making processes and (ii) to provide guidelines for the elicitation of preference parameters of the S-RMP ranking method. The results highlight that the proposed method opens a promising line of research in the environmental decision-making domain, thanks to its ability to use heterogeneous information consistently with the increasing amount of qualitative data embedded in real decision-making processes.

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1. Introduction

Preferences are fundamental to decision processes, since the recommendations are meaningful and acceptable only if the decision makers' (DM) values are taken into consideration. Within this context, a challenging activity is "preference elicitation", which aims to capture the DMs' preferences in order to accurately specify the decision model parameters. The challenge is linked to the nature of the preferences expressed by the DMs, which can be imprecise, conflicting, unstable, time-dependent; yet they should be structured and synthesized. More precisely, preference elicitation is the process by which an analyst and a DM interact to fix the parameters of a preference model. The *indirect elicitation* approach avoids asking the DM to express her preferences in terms of numerical values for the considered parameters, but rather requires her to provide partial results she would like to obtain as an output of the preference model from which recommendations are constructed. To support the elicitation of stakeholders' preferences, many models, procedures and methodologies have been proposed (e.g. Mousseau and Pirlot, 2015; Mousseau and Słowiński, 1998; Siskos and Tsotsolas, 2015), which try to cope with the proliferation of semi-automated computerized interfaces and the use of increasingly large datasets.

In this paper we are interested in showing the benefits of using a recent multiple criteria ranking method, named Simple Ranking with Multiple Points (S-RMP, see Bouyssou and Marchant, 2013; Rolland, 2008, 2013; Zheng et al., 2012), to support complex decision-making processes. This ranking method is based on pairwise comparisons, but instead of directly comparing pairs of alternatives, it rather compares the alternatives to a set of predefined reference points. The idea is to construct the global preference relation between two alternatives on the basis of their relative comparisons with specified reference points.

Implementing the S-RMP ranking method to support a decision making process requires to elicit the decision maker's preferences and to set the values of preference parameters involved in the S-RMP method. Interacting with the decision maker directly on the values of the preference parameters is not recommended; *indirect elicitation* can proceed in computing the preference parameters values which best match holistic pairwise comparisons of alternatives provided by the DM. Within this paper, we are using two such algorithms to infer the parameters of the S-RMP method. The first algorithm is based on mathematical programming (exact

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algorithm, feasible only when a small number of holistic pairwise comparisons is considered). The second algorithm is grounded on a metaheuristic, which does not guarantee to find the model that best matches with the provided preferences, but is computationally more effective. The paper tests both algorithms to investigate how useful and efficient they are in practice.

Our context of application is an ex-post simulation of a decision process developed making use of publicly available data for the area under analysis. Through the simulation process we organized 3 focus groups for the elicitation of preference information. During these focus groups, the task of the involved participants was to establish a preference order (ranking) on a set of alternative sites for the location of a new landfill on the basis of different criteria (e.g. presence of population, hydrogeological vulnerability, etc).

In this study we seek to show how the two previously mentioned disaggregation approaches (exact inference and metaheuristic approach) are able to elicit and represent the DMs' preferences in order to provide sound recommendations. The proposed approaches are characterized by the ability to take into account: *i)* the ordinal qualitative evaluation involved in the decision problem, *ii)* the inconsistency that may emerge from the presence of different participants (stakeholders) and *iii)* the presence of a relatively large amount of information and data. The objectives of the study are thus twofold. Firstly, to show on a real world case study how to effectively develop and apply a decision support process which makes use of the S-RMP ranking method, focusing in particular on the preference elicitation aspect, which is indeed the most challenging part in any decision making process. Secondly, we will focus on the question of how to elicit the preference parameters of the S-RMP method in order to be effective and practice oriented.

The remainder of this paper is organized as follows. Section 2 positions this research in the environmental decision making context, by reviewing its present complexities and explaining the need for a new generation of Decision Support Systems. Section 3 contextualizes the decision process under analysis. Section 4 provides the methodological background for the S-RMP method. Section 5 explains the overall decision process proposed by the authors for the use of the S-RMP method in practice. In Section 6, we discuss the obtained results. Finally, Section 7 draws the conclusions and develops insights on how to use the S-RMP method in environmental decision-making processes.

2. Complexities and requirements in environmental decision making

There are several complexities in environmental decision making (SteeleCarmel et al., 2009) that may explain the need for decision support systems, from both technical and social perspectives (Ferretti and Montibeller, 2016; Geneletti and Ferretti, 2015).

Starting from a technical perspective, a first complexity is related to the selection of the method/approach to be used to support the decision making process. While several approaches are possible, Multi Criteria Decision Analysis (MCDA) seems to be a particularly promising one in the context of environmental decision making (e.g Huang et al., 2011). MCDA is an umbrella term to describe a collection of formal approaches which seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter. However, the selection of which approach to use in a specific decision making context is not a trivial one and this choice needs to be based on the specific characteristics of the problem under analysis (see for guidelines Roy and Słowiński, 2013 and Ferretti and Montibeller, 2016). Another complexity is linked to the fact that some of the criteria to be considered in the assessments cannot be easily converted into a monetary value, partly because environmental concerns often involve ethical and moral principles that may not be related to any economic use or value (Kiker et al., 2005), partly because of the difficulties of monetising intangibles (Gregory et al., 1993). This complexity thus leads to a frequent presence of qualitative data/criteria (Lippe et al., 2011; Munda, 2006; Parsons and Dohnal, 1995) in environmental decision-making processes. Thirdly, the spatial dimension of both the alternatives and the characteristics of the territory plays a crucial role in spatial planning (Worall, 1991). Fourtly, the increasing volume, variety and velocity of information (the "*big data*" perspective, McAfee et al., 2012) available to support decision making processes emphasizes the need to develop tractable methods for the aggregation of the information in a way which is meaningful for planners and decision makers (Kiker et al., 2005). Nowadays, factors such as technological advances for monitoring systems and the availability of Geographic Information Systems create increased accessibility and availability of data for environmental planning and decision making (Malczewski, 2006). These increasingly big datasets generate the necessity to collect many preference information from the DMs and experts, who usually have very limited amount of time.

These technical complexities of decision making processes may explain the growing use of multi criteria analysis for environmental decision making (see Huang et al., 2011; Kiker et al., 2005; Mustajoki et al., 2004; Reichert et al., 2013; Zendehdel et al., 2009), as well as the increased interest towards preference learning algorithms (Mousseau and Pirlot, 2015).

From a social perspective, there are again several complexities in the environmental decision making context (Ferretti and Montibeller, 2016). Firstly, such decision processes often involve many different stakeholders, with different objectives and priorities, thus representing exactly the type of problem that behavioral decision research has shown humans are poorly equipped to solve unaided (Kiker et al., 2005) and leading to an increased demand for justification, legitimation and accountability of decisions (Tsoukiàs et al., 2013). Secondly, complex decision problems typically draw on multidisciplinary knowledge bases, incorporating natural and social sciences, as well as medicine, politics, and ethics (Munda, 2006). Thirdly, and associated with the previous complexity, is the tendency of planning issues to involve shared resources, which means that group decision processes are often necessary (Kiker et al., 2005). However, groups are also susceptible to establish entrenched positions (defeating compromise initiatives) or to prematurely adopt a common perspective that excludes contrary information and suffers from "groupthink" (e.g Kiker et al., 2005). These social complexities may explain the increasing adoption of participative decision processes in those contexts and of facilitated decision modelling to support them. Finally, one of the most relevant complexities in environmental decision-making processes is the inherent trade-off between socio-political, environmental, ecological and economic factors (Keeney, 2013). This complexity has indeed both technical and social roots as it calls for the understanding of heterogeneous scales of impacts, deals with values and conflicting points of view and involves the possibility of behavioral biases (Hämäläinen, 2015).

Following from these considerations, the need for decision support systems able to (i) facilitate inclusion of different perspectives, (ii) handle qualitative data without the need to convert performances into a quantitative scale and (iii) learn the parameters of the model from a limited set of preference information in order to keep the cognitive burden on the decision makers as limited as possible can be highlighted. The research presented in this paper is an attempt in this direction.

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