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Tackling uncertainty in multi-criteria decision analysis – An application to water supply infrastructure planning

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ABSTRACT

We present a novel approach for practically tackling uncertainty in preference elicitation and predictive modeling to support complex multi-criteria decisions based on multi-attribute utility theory (MAUT). A simplified two-step elicitation procedure consisting of an online survey and face-to-face interviews is followed by an extensive uncertainty analysis. This covers uncertainty of the preference components (marginal value and utility functions, hierarchical aggregation functions, aggregation parameters) and the attribute predictions. Context uncertainties about future socio-economic developments are captured by combining MAUT with scenario planning. We perform a global sensitivity analysis (GSA) to assess the contribution of single uncertain preference parameters to the uncertainty of the ranking of alternatives. This is exemplified for sustainable water infrastructure planning in a case study in Switzerland. We compare 11 water supply alternatives ranging from conventional water supply systems to novel technologies and management schemes regarding 44 objectives. Their performance is assessed for four future scenarios and 10 stakeholders from different backgrounds and decision-making levels. Despite uncertainty in the ranking of alternatives, potential best and worst solutions could be identified. We demonstrate that a priori assumptions such as linear value functions or additive aggregation can result in misleading recommendations, unless thoroughly checked during preference elicitation and modeling. We suggest GSA to focus elicitation on most sensitive preference parameters. Our GSA results indicate that output uncertainty can be considerably reduced by additional elicitation of few parameters, e.g. the overall risk attitude and aggregation functions at higher-level nodes. Here, rough value function elicitation was sufficient, thereby substantially reducing elicitation time.

1. Introduction

1.1. Consideration of uncertainty in MAUT applications

Over the past decade, the number of applications of multi-criteria decision analysis (MCDA) and more specifically, multi-attribute utility theory (MAUT) and multi-attribute value theory (MAVT) (e.g. Keeney, 1982; Keeney & Raiffa, 1993), has considerably increased in the environmental sciences (Ananda & Herath, 2009; Huang, Keisler, & Linkov, 2011). This is also the case in other disciplines (Wallenius et al., 2008). In MAUT applications, strong simplifying assumptions are often made to keep elicitation and modeling of preferences feasible given the available resources. Common simplifications are a) the choice of additive MAUT models (Hajkowicz, 2008; Hyde, Maier, & Colby, 2005; Joubert, Stewart, & Eberhard, 2003), b) use of linear marginal value functions (Raju & Vasan, 2007; Weber, 1987), c) assumption of risk neutrality, as well as d) neglecting uncertainty of model parameters (e.g. "weights"), attributes, and boundary conditions such as socio-economic change (Hyde, Maier, & Colby, 2004; Martin, Bender, & Shields, 2000; Torrance et al., 1996). The reasons are manifold, e.g. higher model comprehensibility for decision makers, time constraints, and the need for cognitively tiring repetitive assessments (Karvetski, Lambert, & Linkov, 2009a; Stewart, 1995), but often remain undisclosed. Although the necessity of a systematic consideration of uncertainty has been widely acknowledged in theory (e.g. Butler, Jia, & Dyer, 1997; Durbach & Stewart, 2011, 2012b; French, 2003; Kangas & Kangas, 2004; Keeney & Raiffa, 1993; Stewart, 1995, 2005), it is commonly not considered in practice.

1.2. Sources of uncertainty

Different sources of uncertainty in MCDA are discussed in the literature. These cover uncertainties arising from (1) problem framing and structuring, (2) attribute prediction, and also (3) components

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of the preference model, i.e. in the case of MAVT and MAUT: (3a) the choice of hierarchical aggregation functions, (3b) the form of the marginal value/utility functions, and (3c) the corresponding aggregation parameters ("weights"). Furthermore, many of the commonly used preference elicitation techniques lack robustness towards biases (Bleichrodt, Pinto, & Wakker, 2001; Borcherding, Eppel, & von Winterfeldt, 1991; Morton & Fasolo, 2009; Weber & Borcherding, 1993), constituting an additional source of uncertainty.

By using the word "uncertainty" in this paper, we make no distinction between uncertainties elsewhere referred to as *risk* (known cause–effect, probabilistically quantifiable), *uncertainty* (known cause–effect, not probabilistically quantifiable), and *ignorance* ("deep uncertainty", unknown cause–effect, not quantifiable). Other classifications distinguish between *aleatory uncertainty* (due to randomness, see *risk*) and *epistemic uncertainty* (due to lack of knowledge, sometimes quantifiable). Instead, we use the term *uncertainty* when referring to "knowledge gaps or ambiguities that affect our ability to understand the consequences of decisions" (Gregory et al., 2012, p. 127), i.e. the way it is used in common language.

(1) **Problem framing and structuring:** Problem framing and structuring concerns the definition of the decision problem and boundary conditions, a stakeholder analysis to establish participation, and the development of the system of objectives and a set of alternatives for evaluation (Belton & Stewart, 2002; Keeney, 1982). Uncertainties arising from problem structuring are hardly quantifiable. People arrive at different decisions for the same problem dependent on the problem framing (Belton & Stewart, 2002; Morton & Fasolo, 2009). Different hierarchical structuring of the same system of objectives has been shown to affect the assigned weights (due to "splitting bias", e.g. Weber & Borcherding, 1993). Additionally, the number of identified fundamental objectives is linked to how well decision makers are supported during the formulation of fundamental objectives (Bond, Carlson, & Keeney, 2008, 2010). Thorough structuring is thus indispensable. An overview of structuring methods is given in e.g. Belton and Stewart (2010) and Franco and Montibeller (2011). A growing trend in MCDA is to address uncertainties about future framework boundary conditions that are beyond the influence of decision makers with scenario analysis (e.g. Goodwin & Wright, 2001; Montibeller, Gummer, & Tumidei, 2006; Stewart, French, & Rios, 2013).

(2) **Attribute prediction:** The sources of uncertainty about the attribute levels of each decision alternative depend on the assessment process. Uncertainty can arise from the imprecision of quantitative elicitation and formulation of expert estimates which is prone to biases (Ayyub, 2001; Cooke, 1991; Kynn, 2008; O'Hagan et al., 2006). It can also stem from the uncertainty of model predictions such as uncertainty of model input/structure/parameters (see e.g. French, 1995; Refsgaard, van der Sluijs, Højberg, & Vanrolleghem, 2007; Walker et al., 2003).

(3) **Hierarchical aggregation function:** The multi-attribute value or utility function is typically structured hierarchically (see later example, Fig. 1). The value or utility of the main objective depends on lower-level utility or value functions. These may directly depend on the attributes ("marginal utility or value functions") or indirectly through intermediate aggregation functions. The uncertainty about the hierarchical aggregation function is governed by the lack of knowledge about which independence conditions are satisfied by the decision maker's preferences (Eisenführ, Weber, & Langer, 2010; Keeney & Raiffa, 1993), and the precision of other aggregation model parameters. The additive, multiplicative, and multi-linear models are presented in Keeney and Raiffa (1993). The first requires *mutual preferential independence*, *additive independence*, and either *difference independence* (for values) or *mutual utility independence* (for utilities) to hold (Eisenführ et al., 2010). The second model does not require additive independence. The third model requires the weakest assumptions, but easily becomes infeasible due to non-identifiability of its parameters (Stewart, 2005). Other less common models are the Cobb–Douglas model (i.e. the weighted geometric mean, originally suggested as a production function but later also used in the current context; Cobb & Douglas, 1928), minimum-models, or mixtures of these (e.g. Langhans, Lienert, Schuwirth, & Reichert, 2013; Langhans, Reichert, & Schuwirth, 2014; Schuwirth, Reichert, & Lienert, 2012).

(4) **Marginal ("single-attribute") value or utility functions:** Uncertainty about the shape of value and utility functions also arises from the imprecision of preferences, as well as inconsistencies and elicitation biases. Following von Neumann and Morgenstern (1947), in Eisenführ et al. (2010) and Dyer and Sarin (1979), we differentiate between (measurable) value functions and (ordinal) utility functions. Value functions describe preferences regarding sure attribute outcomes. Utility functions are used to rank "risky" attribute outcomes (the uncertainty of which is quantifiable by probability distributions). Utility functions are either directly elicited (Hershey & Schoemaker, 1985; Wakker & Deneffe, 1996) or obtained from converting value functions to utility functions given a specific intrinsic risk attitude (Dyer & Sarin, 1982). Again, several biases are known. For assigning values: *scope insensitivity* and *reference point effects* (e.g. Morton & Fasolo, 2009), and for the assessment of utilities (Bleichrodt et al., 2001; Cox, Sadiraj, Vogt, & Dasgupta, 2012; Eisenführ et al., 2010): *non-linear weighting of probabilities* (Kahneman & Tversky, 1979), *ambiguity aversion* (Ellsberg paradox; Ellsberg, 1961), and *certainty effects* (Allais paradox; Allais, 1953). In the absence of bias-free elicitation methods, some have questioned the use of expected utility theory (e.g. Abdellaoui, Bleichrodt, & Paraschiv, 2007;Cox et al., 2012; Rabin, 2000; Schmidt, Starmer, & Sugden, 2008). Others developed approaches to correct for biases (Bleichrodt et al., 2001) or simply accept some degree of descriptive deviation from theory in prescriptive decision analyses (e.g. French, 2003; Stewart, 2005).

(5) **Aggregation parameters ("weights"):** Uncertainty and imprecision of the weights are related to the articulated accuracy and consistency of judgments (Jessop, 2011). The elicitation of weights is prone to biases, such as the *splitting bias*, *range effect*, and *hierarchical effects* (Morton & Fasolo, 2009; Weber & Borcherding, 1993). Comparing four weight elicitation methods, Borcherding et al. (1991) judge none to be internally more consistent or less biased than the others, and suggest doing more consistency checks. Mustajoki et al. (2005) and Jessop (2011) argue that the assumption of exact weights imposes a precision not represented by the stakeholder's preferences and recommend using imprecise or interval weights instead. Using imprecise weights also reduces inconsistencies within and between elicitation methods. Hierarchical elicitation (e.g. Pöyhönen, Vrolijk, & Hämäläinen, 2001) and ex post corrections (Jacobi & Hobbs, 2007) have been suggested to minimize the splitting bias.

1.3. Uncertainty and sensitivity analysis

Although often interchangeably used, the term *uncertainty analysis* refers to the quantification of model output uncertainty through propagation of uncertainty of model parameters and inputs (French, 2003), and *sensitivity analysis* to "the study of how uncertainty in the output [. . .] can be apportioned to different sources of uncertainty in the model input" (Saltelli, Tarantola, Campolongo, & Ratto, 2004). Global sensitivity analysis (GSA) allows inputs to vary according to a given probability distribution, whereas local sensitivity analysis (LSA) uses a linearization of the model at a pre-defined point in parameter space (Saltelli, 2008). Uncertainty and sensitivity analyses address a