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Dominance intensity measure within fuzzy weight oriented MAUT: An application

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ABSTRACT

We introduce a dominance intensity measuring method to derive a ranking of alternatives to deal with incomplete information in multi-criteria decision-making problems on the basis of multi-attribute utility theory (MAUT) and fuzzy sets theory. We consider the situation where there is imprecision concerning decision-makers' preferences, and imprecise weights are represented by trapezoidal fuzzy weights. The proposed method is based on the dominance values between pairs of alternatives. These values can be computed by linear programming, as an additive multi-attribute utility model is used to rate the alternatives. Dominance values are then transformed into dominance intensity measures, used to rank the alternatives under consideration. Distances between fuzzy numbers based on the generalization of the left and right fuzzy numbers are utilized to account for fuzzy weights.

An example concerning the selection of intervention strategies to restore an aquatic ecosystem contaminated by radionuclides illustrates the approach. Monte Carlo simulation techniques have been used to show that the proposed method performs well for different imprecision levels in terms of a hit ratio and a rank-order correlation measure.

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1. Introduction

Most complex decision-making problems involve imprecise information [58]. It is frequently impossible to predict with certainty the alternative performances, since as they often reflect social or environmental impacts or are taken from statistics or measurements, they may be intangible.

Neither is it easy to elicit the relative importance of criteria by means of precise weights. Decision makers (DMs) may find it difficult to compare criteria or not want to reveal their preferences in public. Furthermore, in a group decision-making context, imprecision concerning preferences may be the result of a negotiation process. This situation is usually referred to as decision-making with imprecise information, with incomplete information or with partial information [49,50].

A number of papers on multi-attribute utility theory (MAUT) have dealt with incomplete information. For instance, Sage and White [54] proposed the model of *imprecisely specified multi-attribute utility theory* (ISMAUT), where preference information about both weights and utilities is assumed not to be precise. Malakooti [38] suggested a new efficient algorithm for ranking alternatives when there is incomplete information about the preferences and the value of the alternatives. Ahn [1] extended Malakooti's work.

More recently, Jiménez et al. [29] accounted for missing information about some alternative performances. They proposed using the attribute range rather than redistributing the respective weights throughout the objective hierarchy.

Another possibility for dealing with imprecision within MAUT described in the literature attempts to apply the concept of pairwise and absolute dominance to eliminate inferior alternatives, leading to the so-called surrogate weighting methods [60,4], and adapted classical decision rules [46,56], respectively.

Eum et al. provided linear programming characterizations of dominance and potential optimality for alternatives when information about performances and/or weights is incomplete [21]. Lee et al. extended the approach to hierarchical structures [37], and Park developed the concepts of weak potential optimality and strong potential optimality [45]. In [39], the more general case considering imprecision, described by means of fixed bounds, appears in alternative performances, as well as in weights and utilities.

More recently, different dominance measuring methods, which use information about each alternative's intensity of dominance, have been proposed [2,41,40].

On the other hand, *stochastic multi-criteria acceptability analysis* (*SMAA*) is based on exploring the weight space in order to describe which scores would make each alternative the preferred

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option. Inaccurate or uncertain criteria values are represented by probability distributions and partial preference information. The *SMAA-2* method [34] extended the original *SMAA* by considering all ranks in the analysis, and *SMAA-O* [36] was designed for problems where information for some or all criteria are ordinal. Different ways of handling dependent uncertainties within *SMAA-2* have been analyzed in [35].

Sarabando and Dias [57] gave a brief overview of approaches proposed within the MAUT and MAVT (Multi-Attribute Value Theory) framework to deal with incomplete information.

The *analytical hierarchy process* (*AHP*) is another popular method, apart from MAUT, when the information on criteria is mainly cardinal and where attributes are fully compensatory. Incomplete information within AHP has also been addressed in the literature, such as [53], where an interval of numerical values is associated with each judgment in the pairwise comparisons or [33,25], dealing with missing data in *AHP*.

Outranking methods [5,23,44] overcome the assumption that attributes are fully compensatory and there is a true ranking of alternatives just waiting to be discovered. The most widely used outranking methods are *ELECTRE* and *PROMETHEE*. *ELECTRE III* improved *ELECTRE II* to deal with inaccurate, imprecise, uncertain and ill-determined data, while *PROMETHEE III* is based on intervals.

Studies concerning imprecision were also conducted using the theory of fuzzy sets [8,30], counting on the advances of research in arithmetic and the logical operators of fuzzy numbers, such as [62], suggesting the comparison of fuzzy numbers using a fuzzy measure of distance [17], proposing the non-additive fuzzy integral when there is dependence among criteria; or [43], introducing ordered weighted aggregation operators.

A modified fuzzy version of *TOPSIS* was proposed in [11], whereas [47] introduced a new specification of a fuzzy model, the fuzzy utility model which is applied for road route choice.

Preliminary works on the extension of *AHP* [13] to account for fuzzy numbers were proposed in [64,6]. A fuzzy integrated hierarchical decision-making approach was developed in [13] to solve the distribution center location selection problem. A fuzzy extension of *AHP*, *FEAHP*, is provided in [12] to deal with the selection of global suppliers, where triangular fuzzy numbers are used in the DMs' comparison judgements, whereas the final priority of the considered criteria is based on a fuzzy synthetic extent analysis [14].

Developments related to fuzzy outranking methods, such as the utilization of the *PROMETHEE* method with trapezoidal fuzzy numbers proposed in [24] are reviewed in [7]. More recently, an extension of the *ELECTRE I* method for group decision-making in a fuzzy environment was introduced in [26].

In this paper we introduce a dominance measuring method that adapts the proposal in [41,27] to account for fuzzy weights, exploiting research reported in [62] on distances between fuzzy numbers based on the generalization of the left and right fuzzy numbers [19,3].

In Section 2 we review dominance-measuring methods proposed to deal with incomplete information within MAUT, which can be viewed as the groundwork of the proposed method. In Section 3 we outline the dominance-measuring method accounting for trapezoidal fuzzy weights. The approach is illustrated in Section 4 using an example concerning the selection of intervention strategies to restore an aquatic ecosystem. In Section 5, the performance of the proposed method is analyzed using Monte Carlo simulation techniques. Finally, some conclusions are discussed in Section 6.

2. Dominance-measuring methods

As cited in the previous section, one option described in the literature for dealing with imprecision within MAUT is to eliminate inferior alternatives based on the concept of dominance.

Let us consider a decision-making problem with m alternatives, A_i, $i=1,\ldots,m$, and n attributes, X_j, $j=1,\ldots,n$, where incomplete information about input parameters was incorporated into the decision-making process. U_i ($\mathbf{u}_i=(u_{i1},\ldots,u_{in})\in U_i$) define the feasible region for utilities associated with alternative A_i over each attribute. Different methods can be used to build utility functions depending on the level of knowledge and features of the attribute under consideration. When there is in-depth and precise knowledge about the attribute, the DM can directly construct a piecewise linear utility function by providing the best and the worst attribute values and some intermediate values with their respective imprecise utilities. Methods based on lotteries, such as *fractile method* and the *extreme gambles method* [22], are used when DMs have little knowledge about or are inexperienced in the domain. The GMAA decision support system, which includes the combination of two slightly modified standard procedures for utility assessment, is introduced in [28]. Incomplete information is entered as value intervals in response to the probability questions that the DM is asked, checking for consistency.

On the other hand, W defines the feasible region for weights, representing the relative importance of criteria as follows:

- ordinal relations, $\mathbf{w}\in W=\{\mathbf{w}=(w_1,\ldots,w_n): w_1\geq w_2\geq\ldots\geq w_n\}$,
- value intervals, $\mathbf{w}\in W=\{\mathbf{w}=(w_1,\ldots,w_n): w_j\in[w_j^L,w_j^U], j=1,\ldots,n\}$,
- intervals for weight ratios (trade-offs), $\mathbf{w}\in W=\{\mathbf{w}=(w_1,\ldots,w_n): w_j/w_k\in[w_{jk}^L,w_{jk}^U], j=1,\ldots,n\}$,
- linear inequality constraints for weights, $\mathbf{w}\in W=\{\mathbf{w}=(w_1,\ldots,w_n): Aw\leq c\}$, or
- nonlinear inequality constraints for weights, $\mathbf{w}\in W=\{\mathbf{w}=(w_1,\ldots,w_n): g(w)\leq 0\}$.

There are many weighting methods that use different questioning procedures to elicit weights, such as *SWING weighting* and *SMARTS* [20], *pricing out method* and *TRADEOFFS weighting* [31], *AHP* [52], or *preference programming* [55]. Most are adapted to account for imprecision.

We assume an additive model, which is considered a valid approximation in most real decision-making problems for the reasons described in [48,59] , and is widely used within MAUT,

$$u(A_i)=\sum_{j=1}^{n} w_j u_{ij}=\mathbf{w}^T\mathbf{u}_i.$$

Given two alternatives A_k and A_l, the alternative A_k dominates A_l if $D_{kl}\geq 0$, D_{kl} being the optimum value of the optimization problem:

$$\begin{aligned} D_{kl}=\min\{&u(A_k)-u(A_l)=\mathbf{w}^T(\mathbf{u}_k-\mathbf{u}_j)\}\\ \text{s.t. }\ &\mathbf{u}_k\in U_k,\mathbf{u}_j\in U_j\\ &\mathbf{w}\in W. \end{aligned}\tag{1}$$

This concept of dominance is called *pairwise dominance*. Another type of dominance, known as *absolute dominance*, can be employed [56]. Absolute dominance considers the following optimization problems:

$$U_k=\max\{u(A_k)=\mathbf{w}^T\mathbf{u}_k\,|\,\mathbf{w}\in W,\mathbf{u}_k\in U_k\}\quad\text{and}$$

$$L_k=\min\{u(A_k)=\mathbf{w}^T\mathbf{u}_k\,|\,\mathbf{w}\in W,\mathbf{u}_k\in U_k\}.$$

Alternative A_k absolutely dominates A_l if $L_k\geq U_l$, i.e., the lower bound of A_k exceeds the upper bound of A_l. Note that if A_k absolutely dominates A_l, then A_k dominates A_l, but the reverse does not hold.

Note that this dominance approach often results in almost no prioritization of alternatives or too many non-dominated

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