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A dynamic multi-criteria decision making model with bipolar linguistic term sets

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ABSTRACT

Real world decision making problems under uncertainty face different challenges. These challenges include lack of information, the necessity of quick decisions, and problems may change across time. When the uncertainty involved is due to fuzziness and vagueness, the use of fuzzy linguistic information can facilitate the elicitation of decision makers' preferences of alternatives by allowing assessment of alternatives in unipolar scales. However, in some cases decision makers need to express negative, positive and neutral attitudes that cannot be modeled by unipolar scales. This paper aims at developing a dynamic linguistic multi-criteria decision making model dealing with bipolar linguistic scales in which both alternatives and criteria may vary across time. In order to consider the historical evolution of alternatives leading up to the current assessments, a fusion process based on transformation functions and uninorm aggregation operator is proposed to deal with the membership functions of bipolar linguistic assessments. Finally the performance of this model is compared with a non-dynamic method in a supplier selection problem.

1. Introduction

Multi-criteria decision making (MCDM) pervades human's lives. In the scheme of MCDM, the decision makers assess several alternatives under a given set of criteria, and select the best one that they prefer (Hwang & Yoon, 2012; Kahraman, Cevik-Onar, & Oztaysi, 2015). Some MCDM problems are time dependent thus the decision makers need to make decisions over time. This is called the dynamic multi-criteria decision making (DMCDM) (Campanella & Ribeiro, 2011; Chang, Ho, Cheng, & Chen, 2006; Jassbi, Ribeiro, & Varela, 2014).

The complexity of DMCDM under uncertainty has made the necessity of developing different proposals to deal with the role of time and modeling of preferences. Saaty (2007) extended the AHP/ANP to dynamic environment. Dynamic multi-attribute decision making with intuitionistic fuzzy information is dealt with in (Su, Chen, Xia, & Wang, 2011; Xu & Yager, 2008). In Yan, Liu, Liu, and Wu (2015) a dynamic multi-attribute decision making model with gray numbers is proposed. There is also some research that focuses on practical applications of DMCDM, such as the ERP selection (Gürbüz, Alptekin, & Alptekin, 2012), supplier selection (Jassbi et al., 2014), distributed manufacturing scheduling (Varela & Ribeiro, 2014), as well as others.

Previous research mainly focuses on the situation in which alternatives and criteria are fixed across time. However, Campanella and Ribeiro (2011) recently introduced a novel DMCDM model that provides a feasible way to deal with DMCDM with non-static alternatives or criteria. It incorporates the temporal information of alternatives by using an aggregation operator with the full reinforcement property. Zulueta, Martínez-Moreno, Pérez, and Martínez (2014) further introduced a discrete time variable index to discriminate alternatives with equal dynamic ratings.

The DMCDM model proposed in Campanella and Ribeiro (2011) has many potential applications, such as the emergency department operation, medical diagnosis, supplier selection, etc. Nevertheless, the model is only suitable for quantitative settings, especially in which assessment values lie in the unit interval. As it has been pointed out in Martínez, Ruan, Herrera, and Herrera-Viedma (2009), Rodríguez, Labella, and Martínez (2016), uncertainty involved in different real world MCDM problems can be satisfactorily modeled and managed by means of fuzzy linguistic information (Zadeh, 1975) which enhances the reliability and flexibility of classical crisp models.

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Usually the linguistic decision models (Doukas & Psarras, 2009; Rodríguez & Martínez, 2013) use linguistic term sets consisting of linguistic terms which are uniformly distributed in a predefined order, and each term is defined by a membership function in the domain [0, 1]. This type of linguistic term set actually uses a unipolar scale. The positive and negative aspects of preferences can be compared and aggregated by this type of scale but the boundary between *good* and *bad* values is not very explicit or defined since their membership functions are both defined on positive partitions of the unit interval. There is also some psychological evidence that many assessment scores of human beings lie on a bipolar scale (Cacioppo, Gardner, & Berntson, 1997; Osgood, Suci, & Tannenbaum, 1957; Slovic, Finucane, Peters, & Macgregor, 2002).

Therefore, it seems productive to include this type of scale in linguistic DMCDM in order to deal with bipolar variables when it is necessary. However, the straightforward application of the model in Campanella and Ribeiro (2011) to a DMCDM problem in a bipolar linguistic environment is impossible because there are no full reinforcement aggregation operators that can be applied to aggregate bipolar linguistic values. Hence, this paper aims at developing a DMCDM model to manage linguistic bipolar scales by using transformation functions between bipolar linguistic terms defined in $[-1, 1]$ and unipolar linguistic terms defined in [0, 1]. The unipolar linguistic terms enable the use of uninorms with a full reinforcement property in dynamic decision process. Finally, the new DMCDM model is applied to a supplier selection problem in comparison with a static MCDM model.

The remainder of this paper is structured as follows. In Section 2, some preliminary research used in this paper is reviewed. In Section 3, the crucial issue of aggregating bipolar linguistic terms is presented. This is then integrated in the DMCDM model dealing with linguistic bipolar scales. In Section 4, an illustrative example is presented to show the performance of the previous DMCDM model. Section 5 concludes the whole paper.

2. Preliminaries

This section reviews Campanella and Ribeiro's DMCDM model (Campanella & Ribeiro, 2011), some concepts about bipolar scales, and the linguistic 2-tuple representation model that will be used for computing linguistic information in our proposal.

2.1. Framework of the dynamic multi-criteria decision making problem

The main feature of the DMCDM model introduced in Campanella and Ribeiro (2011) is that neither alternatives nor criteria are fixed, and decisions are made sequentially across time or just at the end of the decision process.

Let $T = \{1, 2, \ldots\}$ be the set of time periods, A_t be the set of alternatives, and C_t be the set of criteria with weights w_t satisfying $w_t \in [0, 1], \sum_{t \in T} w_t = 1$ at $t \in T$.

At each time $t \in T$, the static rating of alternatives R_t: $A_t \to [0, 1]$ can be obtained by using some aggregation operators. The historical set of alternatives is then defined as

$$H_0 = \emptyset, H_t \subseteq \bigcup_{\substack{t' \le t \\ t' \in T}} A_{t'}, t \in T.$$

At the end of each time period $t \in T$, the final rating of alternatives is calculated as

$$E_t(a) = \begin{cases} R_t(a), & a \in A_t \backslash H_{t-1} \\ D_E(E_{t-1}(a), R_t(a)), & a \in A_t \bigcap H_{t-1} \\ E_{t-1}(a), & a \in H_{t-1} \backslash A_t \end{cases}$$

where D_E is a full reinforcement aggregation operator. It is noteworthy that the choice of this operator is totally independent of the operator in the calculation of static rating.

It is remarkable that the retention policy for historical set and stopping criterion are given in Campanella and Ribeiro (2011). Regarding the retention policy, all alternatives in the past stage can be accumulated, or only the ones that exceed a threshold are kept, or a fixed number of the top alternatives are remembered. The stopping criterion of DMCDM may be very complex depending on unique nature of a given problem.

A key step of the DMCDM model is the aggregation of history and current ratings by using a full reinforcement aggregation operator. Full reinforcement (Ribeiro, Pais, & Simoes, 2010; Yager & Rybalov, 1998a) means that aggregating the high (or low) values will produce a higher (or lower) result than each individual value, which is called upward (or downward) reinforcement, while aggregating a high value and a low value will produce an averaging result. In Yager and Rybalov (1998a) the full reinforcement property of different operators is investigated. There are several types of operators possessing such a property, among which uninorm (Yager & Rybalov, 1998b) is an important one. The full reinforcement property of uninorm has been applied to some studies (Campanella & Ribeiro, 2011; Quesada, Palomares, & Martínez, 2015; Zulueta et al., 2014). The concept of uninorm is reviewed in the following.

Definition 1. (Yager & Rybalov, 1998b) A uninorm is a mapping U: $[0, 1] \times [0, 1] \to [0, 1]$ having the following properties:

1. $U(a, b) = U(b, a)$ (Commutativity);
2. $U(a, b) \ge U(c, d)$, if $a \ge c, b \ge d$ (Monotonicity);
3. $U(a, U(b, c)) = U(U(a, b), c)$ (Associativity);
4. There exists an element $e \in [0, 1]$ called the identity element, such that for all $a \in [0, 1]$, $U(a, e) = a$.

There are different forms of uninorms, among which the triple Π operator (Yager & Rybalov, 2011) is a very useful one. Emilion, Sébastien, and Andrei (2013) generalized the triple Π operator and explored the wide applications of such generalizations.

The triple Π operator U: $[0, 1]^n \to [0, 1]$ is given as

$$3\Pi(x_1, \ldots, x_n) = \frac{\prod_{i=1}^{n} x_i}{\prod_{i=1}^{n} x_i + \prod_{i=1}^{n} (1 - x_i)}$$

The triple Π operator is a uninorm with the identity element 0.5.

A generalization of the triple Π operator with the identity element being valued as any $e \in (0, 1)$ is defined as

$$U_e(x_1, \ldots, x_n) = \frac{\prod_{i=1}^{n} (x_i/e)}{\prod_{i=1}^{n} (x_i/e) + \prod_{i=1}^{n} ((1 - x_i)/(1 - e))} \tag{1}$$

It is proved that U_e is also a uninorm (Yager, 2002). Therefore, it has the full reinforcement property. In our model this operator will be utilized as D_E to aggregate the historical assessment and static rating.

2.2. Bipolar scales

The nature of bipolarity is rooted deeply in human thought. The bipolarity is initially investigated in psychology and the social sciences (Cacioppo et al., 1997; Osgood et al., 1957; Slovic et al., 2002), and later on its applications are widely studied in fuzzy logic, fuzzy integral, fuzzy set, etc. (Benferhat, Dubois, Kaci,