Supporting university career services by means of a multi-criteria decision-aiding system

J. Nguyen, G. Sánchez-Hernández, A. Armisen, N. Agell, X. Rovira, and C. Angulo

Universitat Politècnica de Catalunya (BacelonaTech), Spain
University of Vic, Central University of Catalonia, Spain
ESADE Business School, Ramon Llull University, Spain

***Abstract*—This paper is a reduced version of the one published in [1]. We introduce a linguistic multi-criteria decision-aiding model to match college students with internships. It considers a fuzzy ordered weighted averaging (FOWA) operator to capture the inherent uncertainty and vague nature of personnel selection processes. A software tool is implemented to assess the match between internship requirements and student's preferences by means of linguistic descriptions, and propose positions according to student preferences. A reduced list of internships is presented to help students to decide where to focus their attention.**

***Index Terms*—Decision support systems, Multi-criteria decision-aiding, Hesitant fuzzy linguistic terms, Fuzzy OWA operator, Personnel selection problem**

I. Introduction

Organizations are challenged daily to make complex decisions. These decisions can be subjective, uncertain, and imprecise [2]. For global organizations, human resources personnel selection can be challenging as candidates are disperse and vary in level of knowledge of a topic. Their knowledge is difficult to qualify and changes frequently [3]. Personnel selection is subjective in nature with regards to assigning crisp values to the job requirements and evaluating candidate qualifications. Previous studies have extended MCDA methods to this problem to address its fuzziness [4], [5].

The aim of this paper is to introduce a practical decision support system to assist students with identifying internships related to their interests when searching for a position for the first time. A real case example is implemented with student and job information provided by a university's career services office. In terms of feature representation, the novelty of the application is two-fold. First, the requirements of a position are extracted in an implicit manner and represented via linguistic terms. Second, linguistic terms are also considered to represent students' interests. The model considered for linguistic descriptions is the hesitant fuzzy linguistic model. This model was introduced by Rodriguez et al. in [6] and further developed in [7].

The rest of the paper is structured as follows. First, we discuss tools used in the design of a linguistic MCDA system which include linguistic descriptors, and fuzzy matching and aggregation. Next, we describe the proposed decision support system, provide a real case example, discuss conclusions future research directions.

II. Methodology

Internships may be a student's first experience searching for a position, therefore, it may be difficult for him to express his preferences as a single label. Given this uncertainty, we propose the application of Hesitant Fuzzy Linguistic Term Set (HFLTS) [7] to manage the need for several labels to define preferences.The approach proposed in this paper relies on the use of linguistic terms based on a qualitative absolute order-of-magnitude model [8] that allows us to deal with the imprecision and hesitance involved in decision processes. We will express this model by means of HFLTS introduced by Rodriguez et al. [7].

Let $\mathbb{S}_n$ be a finite set of totally ordered basic terms, $\mathbb{S}_n = \{B_0, \ldots, B_n\}$, with $B_0 < \ldots < B_n$ and the hesitant fuzzy linguistic terms set, $H_{\mathbb{S}_n}$, be the set of all consecutive linguistic basic terms of $\mathbb{S}_n$, i.e. $B_{ij} = \{x \in \mathbb{S}_n \,|\, B_i \leq x \leq B_j\}$ $\forall i, j \in \{0, \ldots, n\}$, with $i \leq j$. In general, each term corresponds to a linguistic label, with B_0 being the term "$None$". For simplicity, we will denote the singleton $B_{ii} = B_i$. The total order in the set of basic terms, $\mathbb{S}_n$, allows us to define a total order in $H_{\mathbb{S}_n}$ based on the lexicographic order such that: given two linguistic terms, $B_{ij}, B_{i'j'} \in H_{\mathbb{S}_n}$, $B_{ij} \leq_L B_{i'j'}$, iff $i < i'$ or $i = i'$ and $j \leq j'$. From this point forward, we consider $H_{\mathbb{S}_n^*}$, a subset of $H_{\mathbb{S}_n}$, which corresponds to the HFLTS obtained when the set of basic elements is $\mathbb{S}_n^* = \{B_1, \ldots, B_n\}$. In addition, in $H_{\mathbb{S}_n}$ we consider the subset inclusion to define the relation *"to be more precise or equal to"*. We say that B_{ij} *is more precise or equal to* $B_{i'j'}$, $B_{ij} \preceq B_{i'j'}$, if and only if, $B_{ij} \subseteq B_{i'j'}$, i.e, $i' \leq i$ and $j \leq j'$.

HFLTS can be used to compare individual's preferences to object's attributes to capture imprecision in decision processes. To this end, we will define an operator matching two basic terms and extend it to the entire set of HFLTS catching all possible combinations of hesitancy in both descriptions.

Definition 2.1: The fuzzy matching operator is the map $* : H_{\mathbb{S}_n} \times H_{\mathbb{S}_n^*} \rightarrow H_{\mathbb{S}_n}$ such that:

1) $\forall B_i \in \mathbb{S}_n$ and $\forall B_j \in \mathbb{S}_n^*$, $B_i * B_j = B_{\min(n, n-(j-i))}$,
2) $\forall B_{ij} \in H_{\mathbb{S}_n}$ and $\forall B_{i'j'} \in H_{\mathbb{S}_n^*}$,
$B_{ij} * B_{i'j'} = \bigsqcup\{B_k * B_l, i \leq k \leq j \text{ and } i' \leq l \leq j'\}$.

Note that, 2. coincides with 1. $\forall B_i \in \mathbb{S}_n$ and $\forall B_j \in \mathbb{S}_n^*$.

Example 2.1: Let us consider that a candidate's preferences are represented by $H_{\mathbb{S}_n^*}$ and the features of each position are represented by $H_{\mathbb{S}_n}$, then given the previously considered HFLTS, $H_{\mathbb{S}_n^*}$, with $n = 3$, the results of the fuzzy matching operator for the basic terms are shown in Table I.

TABLE I
FUZZY MATCHING OPERATOR *

*	**Low** (B_1)	**Medium** (B_2)	**High** (B_3)
None (B_0)	Medium (B_2)	Low (B_1)	None (B_0)
Low (B_1)	High (B_3)	Medium (B_2)	Low (B_1)
Medium (B_2)	High (B_3)	High (B_3)	Medium (B_2)
High (B_3)	High (B_3)	High (B_3)	High (B_3)

Given two k-dimensional different vectors, $X = (X_1, ..., X_k) \in (H_{\mathbb{S}_n})^k$ and $Y = (Y_1, ..., Y_k) \in (H_{\mathbb{S}_n^*})^k$, we analyze the existing matching between these vectors, comparing each component, by means of the fuzzy matching operator $*$, and a FOWA (fuzzy ordered weighted average).

Definition 2.2: Given $X \in (H_{\mathbb{S}_n})^k$ and $Y \in (H_{\mathbb{S}_n^*})^k$, the fuzzy matching between X and Y is defined as:

$$X * Y = (X_1 * Y_1, ..., X_k * Y_k) \in (H_{\mathbb{S}_n})^k$$

For our purpose, we consider the regular increasing monotone (RIM) function, introduced by Yager [9], guided by the linguistic quantifier 'most of'.

The proposed system caters to the interests of students rather than the requirements of a position to help students identify internship offerings which best match their individual interests. To start, profiles are created for each student and position to represent preferences and features of each, respectively. Preferences are student interests elicited from each student and features are requirements determined from each position. To obtain these preferences and features, Latent Dirichlet allocation (LDA) is applied to student curriculum vitaes and intership descriptions. Originally developed by Blei et al. [10], LDA is an unsupervised topic modeling method. Student's preferences are compared with each position's features. The outputs of the decision-making model are internship positions sorted in a manner which represents students preferences.

III. A Real Case Example

In this real case example, the 2016 internship program for the Bachelor of Business Administration at ESADE Business School in Barcelona, Spain, was used to apply the proposed method. The data set was composed of 275 student resumes and 1063 available internships. All resumes and internship descriptions in English were considered. The final data set consisted of 275 students and 549 internships. Student information was limited to the resumes provided for the purposes of the 2016 internship cycle. Internship positions included national and international postings.

To evaluate the advantages and drawbacks of our proposed method, we compare it to: 1) TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and 2) a ranking method based on Hellinger distance. In comparison to the TOPSIS method, our method recommended zero positions to at most 40 users while the TOPSIS method recommended zero positions to at most 55 users, demonstrating that more students received recommendations with our method. The results obtained from a comparison with the Hellinger distance show that the Hellinger method recommended 65 or more positions to the majority of the students, while our method provided more reasonable (i.e.140) recommendations to most students.

IV. Conclusion

In this paper, a new method for sorting internship postings according to student interests has been introduced. This methodology improves existing methods in several ways. First, it proposes to perform a matching between students and internships from the perspective of the job candidate rather than the position. This is the reverse of the more popular matching to find the best candidate for a position. Second, the method considers a FOWA operator in the matching to capture the inherent uncertainty of personnel selection. Lastly, the interests and features of the students and positions are represented as HFLTS, reflecting human tendency to opine with imprecision and hesitance in making decisions. Our methodology can be extended to both sides of the general personnel assignment problem making the process more efficient. A position which is closely aligned with the interests of a job candidate may lead to better job loyalty. Therefore, as future research, we propose to adapt our methodology to other personnel selection environments like headhunting firms, online job boards, and industry human resources to uncover the interests of a job candidate prior to the interview process.

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