Fuzzy Techniques for Personnel Selection

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Abstract

In this paper we use fuzzy logic for decision-making in personnel selection. We show a method in which the OWA aggregation operators enable us to assign different weights to selection criteria to imitate an expert valuation. The company is interested in replicating this system because in a personnel selection that involves many candidates an evaluation process performed by external experts would be too long and expensive. In this context, fuzzy set theory provides some ways of flexibilizing the models to approach mathematical programming to the human thinking.

Keywords: Fuzzy Logic, Personnel Selection, OWA operators.

1. Introduction

Making decisions can determine a high success in companies. If we have a large model, the solution set of alternatives is achieved in two steps: aggregation and exploitation. Aggregation let us use an aggregation operator for getting a collective preference relation [4]. In multi-step problems, we can use some aggregation methods in differents phases. It can be a multi-stage process, where rankings are successively aggregated to produce a final store [11]. Efficient and flexible information aggregation has become a main issue in information access and other multicriteria decision problems in order to handle the large amount of useful information to be processed and the diversity and precision of the information. Aggregations between the min operator and the max operator are interesting in this case, given by the averaging operators [8].

Many well-known aggregation functions are just special cases of the Choquet and Sugeno integrals, that have an important role in multicriteria decision making. For instance, the weighted arithmetic mean and Yager's OWA (Ordered Weighted Average) aggregation operators are the Choquet integrals, while max and min operators are the Sugeno integrals. The boolean max-min functions are also aggregation functions that can be represented by either the Choquet or Sugeno integral [10]. In this case, if a fuzzy measure is useful to satisfy global goals, then the Sugeno integral can better reflect the true meaning of mean or median operators criteria [11].

OWA operators have attracted the interest of researchers. The main reason is their flexibility to model a wide variety of aggregators, because they include weighting vectors and are not defined by a unique parameter. Yager also introduced the concept of orness, that could be defined as how 'orlike' an operator is. Yager interprets the orness measure as a measure of optimism of the decision making process, whereas the measure of andness is a measure of pessimism [5]. The ability to carry out trade-offs between conflicting goals is another attractive feature [11].

Weighted aggregation has been widely used in the fuzzy decision making process, where the weights are used to represent the relative importance that the decisor maker adds to different decision criteria. So, a fundamental aspect of a fuzzy OWA operator is finding the associated weights; the trade-off between the goals and the constraints can be influenced by changing them. The most used weighting aggregation operators are the generalized means, fuzzy integrals or OWA operators [7].

There are three main approaches used to choose weights [9]:

- *Indiference trade-off method*. The user is asked about how many is willing to give up in one attribute to obtain improvements in another, after which the weights are calculated by the given difference judgements.
- *Direct weighting method*. The user gives the relative importance of each attribute. Then, the weights are calculated without considering the trade-off between attributes.
- *Probabilistic equivalence*. It is used to weight utility functions by expressing the probability at which the user is indifferent between an alternative that has probability p of having all attributes with best values and probability *(1-p)* of having attributes with worst values.

In the next section, we show a personnel selection method based in OWA operators and fuzzy logic.

2. Personnel Selection

Personnel selection is the process for selecting a person from among a set of applicants [2]. An accurate personnel selection management adapted under the company circumstances let managers to optimize production costs and to achieve corporative goals [1]. Personnel selection is a complicated management process because of its human nature, and implies focusing in some concepts like validity, trust and criteria fixing. For instance, to validate the selection process, we follow the next steps:

1. Job analysis.
2. Selection of tests, interviews or simulations to measure the knowledge, physics and performance skills that belong to candidates.
3. Application of tests, interviews or simulations.
4. Relating the results with the management' criteria.
5. Checking and testing these proofs with a different group of employees.

If we only use internal valuations (fixed by the company), we must measure distances or candidate similarities with the ideal-candidate. However, an external valuation can complete this internal one and, in this case, the OWA operator techniques are useful [2].

Let us consider an unoccupied post. We must choose between n candidates $Cand = \{P_i\}_{i=1}^{n}$ valued in R competences $\{x_i\}_{i=1}^{R}$. If the company counts on the collaboration of some experts that evaluate the adequacy of a part of the candidate set, we can describe this as follows:

	x_1	x_2	…	x_R	GEV
P_1	a_{11}	a_{11}	…	a_{11}	v_1
P_2	a_{21}	a_{21}	…	a_{21}	v_2
⋮	⋮	⋮		⋮	⋮
P_L	a_{L1}	a_{L1}	…	a_{L1}	v_L
P_{L+1}	$a_{(L+1)1}$	$a_{(L+1)2}$	…	$a_{(L+1)R}$	
⋮	⋮	⋮		⋮	
P_n	a_{n1}	a_{n1}	…	a_{n1}	

where GEV means Global Expert Valuation.

The company is interested in simulating this system because in a personnel selection that involves many candidates an evaluation process performed by external experts would be too long and expensive. Also, the expert best knows his or her own work and is able to value the candidates with a high percentage of success.

The first step consists in trying to discover, at least approximately, the global valuation of every candidate. Since the experts give a global valuation, it is unrealistic to assign weights to every competence. The mean-like operators technique, ordered weighted averaging (OWA), introduced by Yager [12] would be useful.

An OWA operator of dimension n is a mapping $F:\mathfrak{R}^n \to \mathfrak{R}$, that has an associated weighting vector $W=[w_1,,\dots, w_n]^T$ with $\sum_{i=1}^{n} w_i = 1$, $w_i \in [0,1]$, $1 \le i \le n$, such as $F(x_1, x_2, \dots, x_n) = \sum_{k=1}^{n} w_k x_{j_k}$

where x_{j_k} is the *kth* largest element of $x_1, x_2, \dots, x_n$.

By construction, a fundamental aspect of an OWA operator is the re-ordering step. In particular, an aggregate x_i is not associated with a particular weight w_j but rather a weight is associated with a particular ordered position j of the arguments. In fact, this ordering introduces a nonlinearity into the aggregation process (see [3] and [6]).

So, we must first construct a matrix that orders rows from major to minor in order to evaluate candidates.

$$A = \begin{bmatrix} a_{1j_1} & a_{1j_2} & \cdots & a_{1j_R} \\ & \vdots & & \vdots \\ a_{Lj_1} & a_{Lj_2} & \cdots & a_{Lj_R} \\ a_{(L+1)j_1} & a_{(L+1)j_2} & \cdots & a_{(L+1)j_R} \\ & \vdots & & \vdots \\ a_{nj_1} & a_{nj_2} & \cdots & a_{nj_R} \end{bmatrix} \quad (1)$$

where a_{ij_k} represents the *kth* greatest punctuation of the candidate P_i.

To obtain weights that 'copy' the ones considered by the expert, we can solve the next squared programming problem:

$$\begin{aligned} \text{(Ow)} \quad \text{Min} \quad & \sum_{i=1}^{L}\left(\sum_{k=1}^{R} a_{ij_k} w_k - v_i\right)^2 \\ \text{s.t.} \quad & \sum_{k=1}^{R} w_k = 1 \\ & w_k \ge 0, \quad k = 1, \dots, R \end{aligned}$$

The solution of the program (Ow) gives a vector of weights $W = [w_1^*, w_2^*, \dots, w_R^*]^T$ that allows the valuation of all the candidates by using the following expression:

$$v_i^* := \sum_{k=1}^{R} w_k \, a_{ij_k} \quad (2)$$

If we can order the candidates using the values $v^*_1, v^*_2, \ldots, v^*_R$, we have solved our problem, and we have a feasible solution. If there is a draw, we must break the tie with some criteria such as the arithmetic average or the greatest score in some specific competences.

However, in practice the valuation of the competences is done by using tolerance intervals, $I_{ij} = [\alpha_{ij}, \beta_{ij}]$, because it is closer to the human thinking. So, the table which contains the valuations is:

	x_1	x_2	$\ldots$	x_R	GEV
P_1	I_{11}	I_{12}	$\ldots$	I_{1R}	v_1
P_2	I_{21}	I_{22}	$\ldots$	I_{2R}	v_2
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
P_L	I_{L1}	I_{L2}	$\ldots$	I_{LR}	v_L
P_{L+1}	$I_{(L+1)1}$	$I_{(L+1)2}$	$\ldots$	$I_{(L+1)R}$	
$\vdots$	$\vdots$	$\vdots$		$\vdots$	
P_n	I_{n1}	I_{n2}	$\ldots$	I_{nR}	

(3)

As we exposed before, a fundamental aspect is the re-ordering of the valuations. Since the valuations are expressed as intervals, we can distinguish two cases: that in which we suppose that any possible increasing or decreasing of the competences (in I_{ij}) is balanced and that in which we can not assume this hypothesis. Afterward we show two methods to deal with both situations.

1) *Asuming trade-off*

If we accept that there is a trade-off in the competentes of all the candidates, we can write the intervals depending on a parameter:

$$I_{ij} \quad \rightarrow \quad \alpha_{ij} + (\beta_{ij} - \alpha_{ij})\,\delta\,, \qquad \delta \in [0,1],$$

For every value of δ we obtain a matrix $A(\delta)$ which has re-ordered rows in a decreasing way (see (1)). For this δ we solve (Ow) and we obtain the weights, $w_i(\delta)$. According to (2), we can value the candidates for every $\delta \in [0,1]$,

$$v_i^*(\delta) := \sum_{k=1}^{R} w_k(\delta)\, a_{ij_k}\,,\ \delta \in [0,1] \tag{4}$$

The decisor maker has to choose a value of δ more adjusted to his or her needs.

2) *Without a perfect trade-off*

It is necessary to introduce an ordering relation in the set of intervals. We can use the next definition [5]:

DEFINITION 1: Let $A=[a_1, a_2]$, $B=[b_1, b_2] \subset \Re$ be two intervals. A is larger than B, $B \prec A$ if and only if

$$\begin{cases} \dfrac{k_1 a_1 + k_2 a_2}{k_1 + k_2} > \dfrac{k_1 b_1 + k_2 b_2}{k_1 + k_2} & \text{if } k_1 a_1 + k_2 a_2 \neq k_1 b_1 + k_2 b_2 \\ a_1 > b_1 & \text{if } k_1 a_1 + k_2 a_2 = k_1 b_1 + k_2 b_2 \end{cases}$$

where k_1 and k_2 are two positive constants fixed a priori. Notice that if we change $a_1 > b_1$ by $a_2 > b_2$ the order would be less conservative.

We define the intervals of the table (3), as follows

$$a_{ij} = \frac{k_1 \alpha_{ij} + k_2 \beta_{ij}}{k_1 + k_2}.$$

Once we have ordered the values by rows in a decreasing way, we can construct the matrix A (see (1)). Then, we solve model (Ow) and obtain the valuation of the candidates.

Example: We have eight candidates to fill a vacancy. They have been valuated in seven competences:

$$\begin{bmatrix} \tilde{P}_1 \\ \tilde{P}_2 \\ \tilde{P}_3 \\ \tilde{P}_4 \\ \tilde{P}_5 \\ \tilde{P}_6 \\ \tilde{P}_7 \\ \tilde{P}_8 \end{bmatrix} = \begin{bmatrix} 0.4 & [0.5, 0.7] & [0.6, 0.7] & [0.3, 0.5] & 0.8 & [0.2, 0.4] & 0.6 \\ [0.2, 0.4] & 0.6 & [0.7, 0.9] & [0.5, 0.7] & [0.7, 0.8] & [0.2, 0.5] & [0.4, 0.6] \\ [0.4, 0.5] & [0.3, 0.5] & [0.8, 0.9] & 1 & [0.5, 0.6] & 1 & [0.3, 0.5] \\ 0.1 & [0.2, 0.4] & 0.2 & [0.5, 0.6] & [0.6, 0.8] & [0.3, 0.4] & [0.2, 0.5] \\ [0.2, 0.4] & [0.1, 0.3] & [0.5, 0.6] & [0.2, 0.3] & [0.2, 0.5] & 0.2 & [0.8, 0.9] \\ [0.3, 0.4] & [0.5, 0.6] & 1 & [0.3, 0.4] & [0.4, 0.7] & 0.5 & 1 \\ [0.1, 0.3] & 0.8 & [0.4, 0.5] & [0.4, 0.5] & 1 & [0.3, 0.5] & [0.5, 0.7] \\ 0.2 & [0.2, 0.5] & [0.3, 0.5] & [0.5, 0.6] & [0.8, 0.9] & [0.7, 0.9] & [0.3, 0.7] \end{bmatrix}$$

The experts have evaluated the first candidates as follows:

	P_1	P_2	P_3	P_4
Global Valuation	0.6	0.5	0.7	0.4

1) *Asuming trade-off*

We can parametrize every interval depending on a parameter $\delta \in [0,1]$ to obtain:

$$\begin{bmatrix} \tilde{P}_1 \\ \tilde{P}_2 \\ \tilde{P}_3 \\ \tilde{P}_4 \\ \tilde{P}_5 \\ \tilde{P}_6 \\ \tilde{P}_7 \\ \tilde{P}_8 \end{bmatrix} = \begin{bmatrix} 0.4 & 0.5+0.2\delta & 0.6+0.1\delta & 0.3+0.2\delta & 0.8 & 0.2+0.2\delta & 0.6 \\ 0.2+0.2\delta & 0.6 & 0.7+0.2\delta & 0.5+0.2\delta & 0.7+0.1\delta & 0.2+0.3\delta & 4+0.2\delta \\ 0.4+0.1\delta & 0.3+0.2\delta & 0.8+0.1\delta & 1 & 0.5+0.1\delta & 1 & 0.3+0.2\delta \\ 0.1 & 0.2+0.2 & 0.2 & 0.5+0.1\delta & 0.6+0.2\delta & 0.3+0.1\delta & 0.2+0.3\delta \\ 0.2+0.2\delta & 0.1+0.2\delta & 0.5+0.1\delta & 0.2+0.1\delta & 0.2+0.3\delta & 0.2 & 0.8+0.1\delta \\ 0.3+0.1\delta & 0.5+0.1\delta & 1 & 0.3+0.1\delta & 0.4+0.3\delta & 0.5 & 1 \\ 0.1+0.1\delta & 0.8 & 0.4+0.1\delta & 0.4+0.1\delta & 1 & 0.3+0.2\delta & 0.5+0.2\delta \\ 0.2 & 0.2+0.3\delta & 0.3+0.2\delta & 0.5+0.1\delta & 0.8+0.1\delta & 0.7+0.2\delta & 0.3+0.4\delta \end{bmatrix}$$

For instance, we can give the values 0, 0.5 and 1 for the parameter δ and then we can apply the first method. So, we obtain the following weights:

	w_1	w_2	w_3	w_4	w_5	w_6	w_7
$\delta=0$	0.524	0	0	0.191	0	0.285	0
$\delta=0.5$	0.365	0	0.135	0.135	0	0.365	0
$\delta=1$	0.125	0	0.250	0.375	0	0	0.250

Then, we can simulate the external valuation of the candidates as follows:

Candidate	δ=0	δ =0.5	δ =1
P_5	0.514	0.600	0.438
P_6	0.710	0.582	0.625
P_7	0.686	0.700	0.563
P_8	0.533	0.416	0.563

Finally, we order the valuations and conclude that for δ=0, δ=0.5 and δ=1, the candidate P_6, P_3/P_7 and P_3 respectively are choosen.

We can see the solution is different and it depends on the level of additional information.

2) *Without a perfect trade-off*
We order the intervals of valuation according to Definition 1, making k_1= 7 and k_2=5. The model (Ow) provide the following weights:

$$w_1 = 0.406, \quad w_3 = 0.103, \quad w_4 = 0.133$$
$$w_6 = 0.357, \quad w_2 = w_5 = w_7 = 0,$$

By using them, the global valuations are:

	P_5	P_6	P_7	P_8
Global Valuation	0.484	0.654	0.662	0.576

So, the result of the second technique is that the best candidate to choose is P_3.

3. Conclusions

In personnel selection, an inflexible treatment of the candidate valuations can obstruct the ordering process because not all the requirements are considered, while global valuation neutralizes the positive valuation of competences with the negatives, is an unfair process, etc. Fuzzy set theory provides some ways of representing and dealing with this flexibility. We can use it in the constraints to obtain additional trade-offs between improving the objectives and satisfaying the constraints. We represent the uncertainty in the constraints by using generalized formulations of intervals.

In this paper we show a way to reply the experts valuation because in a personnel selection that involves many candidates an evaluation process performed by external experts would be too long and expensive. The techniques explained can be used in other scenarios: hiring, training, promotion, etc., and also can be modelled by means of fuzzy sets. In this framework, fuzzy mathematical methods are a powerful tool for the decision-making process.

Finally, it is worth remarking that the described models can be solved easily by using MS Excel. This is an added advantage because the program is almost universally available.

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