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PERSONNEL SELECTION BASED ON FUZZY METHODS

SELECCIÓN DE PERSONAL BASADA EN MÉTODOS DIFUSOS*

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Abstract

The decisions of managers regarding the selection of staff strongly determine the success of the company. A correct choice of employees is a source of competitive advantage. We propose a fuzzy method for staff selection, based on competence management and the comparison with the valuation that the company considers the best in each competence (ideal candidate). Our method is based on the Hamming

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distance and a Matching Level Index. The algorithms, implemented in the software StaffDesigner, allow us to rank the candidates, even when the competences of the ideal candidate have been evaluated only in part. Our approach is applied in a numerical example.

Keywords: fuzzy sets, personnel selection, management competences.

Resumen

Las decisiones de los directivos en cuanto a la selección de personal determinan en gran medida el éxito de la empresa. Una elección adecuada de los empleados proporciona una ventaja comparativa. Proponemos un método borroso para la selección de personal basado en la gestión de competencias y la comparación con la valoración que la empresa considera más adecuada para cada trabajo (el candidato ideal). Nuestro método utiliza la distancia de Hamming y el Matching Level Index. Los algoritmos, implementados con el software StaffDesigner, nos permite establecer un ranking de candidatos, incluso cuando las competencias del candidato ideal han sido evaluadas tan solo en parte. Nuestro enfoque está aplicado en un ejemplo numérico.

Palabras clave: conjuntos borrosos, conjuntos difusos, selección de personal, gestión de competencias.

Mathematics Subject Classification: 03B52, 68T37, 90B50.

1 Introduction

Nowadays, employees are considered strategic factors and a source of competitive advantage towards generating long run sustainable profits. This is the reason because the strategic management of human resources has become a priority interest of firms. The objective is to have workers perfectly suited to their jobs (Peña Baztán, 1990). As a result, workers will perform excellently, not just satisfactorily, and this will give the company advantage over competitors.

Following the papers of Spencer and Spencer (1993) and Boyatzis (1982), we understand competence as individual knowledge, skills, attitudes and behaviors that result in workers performing certain tasks and duties remarkably well. Competences encompass not only knowledge and experience, but also other human attributes, objective and subjective, more general and more complex (Canós & Liern, 2003).

The process usually begins by identifying the competences, their valuation and the benchmark profile of these competences. Competences help to use a common language in the firm, because as they take into account observable behavior it is easier for the human resource managers and the other managers to agree (Hayes et al., 2000).

This approach makes the comparison between the requirement profile of the job and the competence profile of the candidate, by taking as unit of analysis the individual and not only the work job (Pereda & Berrocal, 1999).

A specific model per firm is implemented in a way that works with a continuous feedback. The quantification difficulties must be taken into account, because standard indicators could not be useful in this case given human nature. Our proposal can be used in the acquisition policies as well as in the developing policies, even when the target is to respect the existing jobs.

In this paper we give a short introduction to management by competences, model that we will use as basis for the proposed algorithms of personnel selection. We propose a method to help in the managers' decision, when the ideal competences associated to the offered job are defined. We apply the method for the case of a development policy in a given firm.

2 Application of fuzzy techniques to human resources management

In order to quantify and objectify the human resource variables, Mathematic Programming techniques are often required to back up decision making and to help managers for carrying out their job as decision makers. However, the enormous number of interactions current firms are subjected to, and how quickly they occur, as well as the uncertainty of many of the available data they use, result in deterministic mathematics being insufficient.

On one hand, to consider all the information the experts have, included the subjective one, can provide benefits. On the other hand, in any decision making process, the used mathematical model will be affected by the introduced numerical values. Some times it is possible to assign probability distribution to some parameters (stochastic uncertainty), but some times, this method is inappropriate, because there is no well-founded reason to assume that the given parameter is following a specific distribution. In that case we will speak about *fuzzy uncertainty* (Zimmermann, 1997, Carlsson & Korhonen, 1986).

In Fuzzy Theory the basic idea is to substitute the characteristic function of a set A, which assigns the value 1 when the element belongs to A and 0 when it does not, by a Membership Function μ_A which associates each element to a real number in the interval $[0, 1]$. The value $\mu_A(x)$ is understood as the membership degree of the element x in A (Kaufmann & Gil-Aluja, 1987). A null membership degree is understood as not membership, 1 is understood as full membership in the Boolean sense, and the intermediate values reflect an uncertainty membership (one speak of partial membership) that will be interpreted in different ways, depending on the case (Zadeh, 1965, Goguen, 1969).

If we consider the referential set X, a common representation of fuzzy sets is the following:

$$\tilde{A} = \{(x, \mu_A(x), x \in X)\}.$$

Fuzzy Theory has been applied to the Human Resources Management in various cases. Despite the variety of cases that can be represented by fuzzy sets, when the value of $\mu_A(x)$ has to be given by one or many experts, one way to make the job of the experts that must valuate easier is to extend the concept of fuzzy set, by admitting $\mu_A(x)$ to be a tolerance interval, this is, a multivaluated membership function

$$\mu^\Phi : X \to P([0,1]),$$

given by $\mu^\Phi(x) = [a_x^1, a_x^2] \subseteq [0,1]$. The set $\tilde{A}^\Phi = \{(x, \mu^\Phi(x)), x \in X\}$ is called interval- valued fuzzy set (Gil-Aluja, 1998). In general, when the referential set is finite, $X = \{x_1, x_2, \ldots, x_n\}$, the way to express it uses to be

$$\tilde{A}^\Phi = \{(x_j, \mu^\Phi(x_j)), j = 1, \ldots, n\}. \quad (1)$$

In this paper we will assume the competences, the ideal competences, as well as the candidates' competences, are valuated with intervals, so we will handle the uncertainty by using interval-valued fuzzy sets or Φ-*fuzzy*. The fuzzy processing for Human Resources Management has the difficulty of using a suitable distance function (Chen & Cheng, 2005) and the difficulty of ordering fuzzy sets according to that distance (Capaldo & Zollo, 2001).

2.1 Measuring distances to an ideal candidate

In order to valuate and rank the candidates for a job, we will study the similarity among each candidate and the ideal candidate (the virtual candidate whose competences have the highest valuation given by the experts) in two different ways, by means of the Hamming distance and by using a Matching Level Index (Dubois & Prade, 2000).

One way of ordering the candidates is to calculate the distance from each of them to the ideal candidate. Other definitions of distance can be considered (Euclidean, Tchebichev, etc.) to select the "best fit", but the Hamming distance has recorded favorable results in ordering fuzzy sets in the literature (Gil-Aluja, 1998).

Definition 1 *Given a reference set* $X = \{x_1, x_2, \ldots, x_n\}$ *and two interval-valued fuzzy numbers* Φ*-fuzzy* $\tilde{A}^\Phi$, $\tilde{B}^\Phi$, *whose membership functions are* $\mu^\Phi_{\tilde{A}}(x_j) = [a^1_{x_j}, a^2_{x_j}]$, $\mu^\Phi_{\tilde{B}}(x_j) = [b^1_{x_j}, b^2_{x_j}]$, $j = 1, 2, \ldots, n$, *the normalized Hamming distance is defined as*

$$\begin{aligned} d(\tilde{A}^\Phi, \tilde{B}^\Phi) &= \frac{1}{n}\left(\sum_{j=1}^{n} |\mu^\Phi_{\tilde{A}}(x_j) - \mu^\Phi_{\tilde{B}}(x_j)|\right) \\ &= \frac{1}{2n}\left(\sum_{j=1}^{n} (|a^1_{x_j} - b^1_{x_j}| + |a^2_{x_j} - b^2_{x_j}|)\right). \end{aligned} \tag{2}$$

Definition 2 *Given a reference set* $X = \{x_1, x_2, \ldots, x_n\}$ *and two interval-valued fuzzy numbers* $\tilde{A}^\Phi$, $\tilde{B}^\Phi$, *whose membership functions are* $\mu^\Phi_{\tilde{A}}(x_j)$, $\mu^\Phi_{\tilde{B}}(x_j)$, $j = 1, 2, \ldots, n$, *the matching level index of the interval-valued fuzzy number* $\tilde{B}^\Phi$ *with respect to the interval-valued fuzzy number* $\tilde{A}^\Phi$ *is defined as*

$$\mu_{\tilde{A}^\Phi}(\tilde{B}^\Phi) = \frac{1}{n}\sum_{j=1}^{n} \mu^{x_j}_{\tilde{A}^\Phi}(\tilde{B}^\Phi)$$

where

$$\mu^{x_j}_{\tilde{A}^\Phi}(\tilde{B}^\Phi) = \begin{cases} 1 & \text{if } [b^1_{x_j}, b^2_{x_j}] \subseteq [a^1_{x_j}, a^2_{x_j}] \\ \frac{length([b^1_{x_j}, b^2_{x_j}] \cap [a^1_{x_j}, a^2_{x_j}])}{length([b^1_{x_j}, b^2_{x_j}] \cup [a^1_{x_j}, a^2_{x_j}])} & \text{if } [b^1_{x_j}, b^2_{x_j}] \not\subseteq [a^1_{x_j}, a^2_{x_j}]. \end{cases} \tag{3}$$

3 Our problem

By personnel selection we understand the process through one or several people that better fit the characteristics of a job are chosen. As in the most cases of management, this process is complicated and it must be taken into account concepts as validation, reliance and fixing of approach.

Specifically, if we consider a job with n appropriated competences, that we will denote as our referential finite set $X = \{c_1, c_2, \ldots, c_n\}$, and we have R possible candidates, Cand $= \{P_1, P_2, \ldots, P_R\}$, to fill the job, the selection should be done by evaluating each candidate in the n competences. This evaluation can be understood as the membership degree to a fuzzy set or Φ-fuzzy set (Canós & Liern, 2008).

Let's assume the R candidates have been valuated in the n competences by a set of p experts, Exp $= \{E_1, E_2, \ldots, E_p\}$, and the valuation of each competence and each expert has been done with intervals. The way to fix the extremes of the intervals is very important. First, it should be easy for the experts to express and quantify their valuation. Second, it must be clear enough to differentiate among the given valuations. In our case, we propose values between 0 and 1, taken with one figure. This is, 11 different values to build the intervals. In some cases could be excessive, but we have checked that an odd number of values, 7 or 9, are adequate.

Once established that point, the firm managers have to fix the most suitable valuation of each competence. In this way, the ideal candidate for the firm is defined. The way to define the ideal candidate is done by means of intervals valuated by other (or the same) set of experts. An applicant will fill better the job as much "similar" to the given ideal candidate is.

Definition 3 *A fuzzy number $\tilde{M}$ is said to be a LR-fuzzy number,*

$$\tilde{M} = (m^L, m^R, \alpha^L, \alpha^R)_{LR}$$

if its membership function has the following form:

$$\mu_{\tilde{M}} = \begin{cases} L\left(\frac{m^L - x}{\alpha^L}\right) & \text{if } x < m^L \\ 1 & \text{if } m^L < x < m^R \\ R\left(\frac{x - m^R}{\alpha^R}\right) & \text{if } x > m^R \end{cases} \tag{4}$$

where L and R are reference functions, i.e. $L, R : [0, +\infty[\to [0, 1]$ are strictly decreasing in supp$\tilde{M} = \{x : \mu_{\tilde{M}}(x) > 0\}$ and upper semi-continuous functions such that

$$L(0) = R(0) = 1.$$

If supp$\tilde{M}$ is a bounded set, L and R are defined on $[0, 1]$ and satisfy $L(1) = R(1) = 0$. If there exist an inverse for the functions L and R, the α-cuts are:

$$M(\alpha) = [M_1(\alpha), M_2(\alpha)] = [m^L - \alpha^L L^{-1}(\alpha), m^R + \alpha^R R^{-1}(\alpha)], \alpha \in [0, 1].$$

In particular, when L and R are linear functions, we are

$$M(\alpha) = [M_1(\alpha), M_2(\alpha)] = [m^L - \alpha^L \alpha, m^R + \alpha^R \alpha], \alpha \in [0, 1].$$

In this paper our interest is, not only to obtain intervals (α-cuts) from a fuzzy number, but also the inverse process, this is, to build fuzzy numbers from the aggregation of intervals. The following lemma gives us the way to do it.

Lemma 1 *Let us consider h intervals $\{[a_r^1, a_r^2], 1 \leq r \leq h\}$ and two reference functions $L, R : [0, +\infty[\to [0, 1]$. Given the values*

$$m^L = \min_r \frac{a_r^1 + a_r^2}{2}, m^R = \max_r \frac{a_r^1 + a_r^2}{2}, M^L = \min_r a_r^1, M^R = \max_r a_r^2,$$

$$\alpha^L = m^L - M^L, \alpha^R = m^R - M^R,$$

$\tilde{M} = (m^L, m^R, \alpha^L, \alpha^R)_{LR}$ is a LR-fuzzy number and the intervals $[m^L, m^R]$ and $[M^L, M^R]$ are the peak and support, respectively, of $\tilde{M}$.

4 Personnel selection model

In the models we are going to work with, the selection is based on n necessary competences for occupying one job. Our referential set is the set of competences

$$X = \{c_1, c_2, \ldots, c_n\},$$

and each candidate will be valuated on them. Let's assume p experts who valuate all candidates on the n competences through intervals.

One very used way for ordering the candidates is to compare them with an ideal candidate (Gil-Aluja, 1998, Canós et al., 2008, Canós & Liern, 2008). Bigger is the intersection among the candidate and the ideal, more suitable is the candidate for the job (Gil-Aluja, 1998). Depending on the job, it would be possible to assign different weights to the competences, although in this paper we will assume all the competences weighted in a similar way. The process to follow is similar in any case.

The Hamming distance calculates the difference between the extremes of the intervals. In this method there is no difference between one excess or one defect with respect to the ideal, so we evaluate both in a similar way. In case of the Matching Level Index, it implicitly includes an adjustment of the excesses or defects. This is the reason because these two techniques can give different results to the same process of personnel selection.

4.1 Comparison with the ideal candidate

As we have seen above, for each $\alpha \in [0,1]$ we have R Φ-fuzzy numbers, $\tilde{P}_i^{\Phi}(\alpha)$, $1 \leq i \leq R$, which represent each one of the candidates, and another one, $\tilde{I}^{\Phi}(\alpha)$, which represents the ideal candidate. The goal is to measure the distance or the similarity of each one of the candidates to the ideal one, by applying the Hamming distance or the Matching Level Index, this is

$$d_i(\alpha) = d(\tilde{P}_i^{\Phi}(\alpha), \tilde{I}^{\Phi}(\alpha)), 1 \leq i \leq R \tag{5}$$

where d represents the Hamming distance (Definition 1) or the Matching Level Index (Definition 2). The process we have followed is given in the scheme showed in Figure 1.

When the set of real numbers $\{d_i(\alpha)\}_{i=1}^{R}$ is ordered, the candidates are ordered for the level α of requirement. If we repeat this process for values

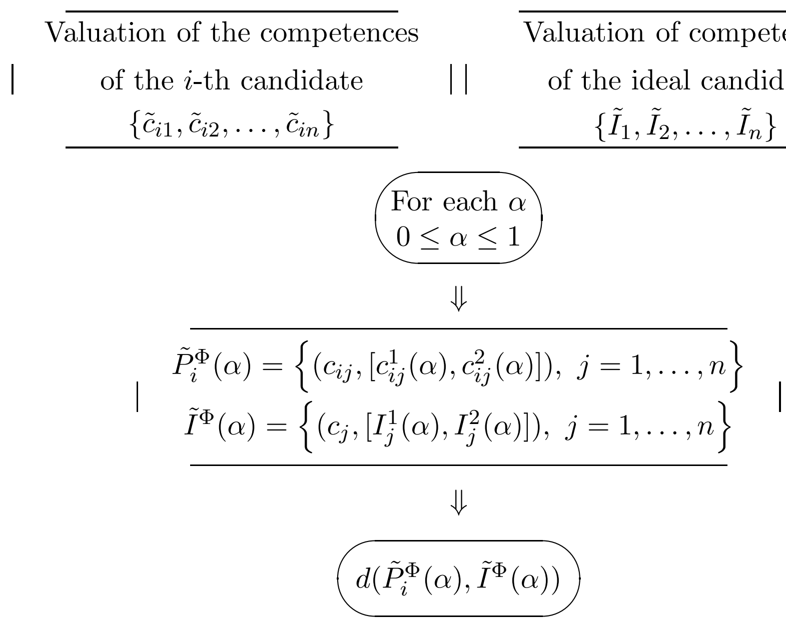

Figure 1: Scheme for the comparison of the candidates with the ideal one.

$\alpha \in [0, 1]$ which are of interest for the decisor, we have an order of the candidates in different cases.

In general, it is possible to offer to the Human Resources Department of the firm different rankings of candidates for different levels of demand $\alpha \in [0, 1]$. Each level of demand determines a final position of the candidates, because the level of requirement could change the valuation of one candidate, depending on his/her situation inside or outside of the stablished level of requirement.

4.2 The algorithm

According to what has been stated above, we have built the following algorithm:

Step 1. Construct a fuzzy number for each one of the competences for the ideal candidate, $\{\tilde{I}_1, \tilde{I}_2, .., \tilde{I}_n\}$, given the valuation of q experts.

Step 2. Construct a fuzzy number for each one of the competences for each candidate, $\{\tilde{c}_{i_1}, \tilde{c}_{i_2}, \ldots, \tilde{c}_{i_n}\}$, from the valuation of p experts.

Step 3. For each one of the competences, and given an exigency level

$\alpha \in [0,1]$, construct interval-valued fuzzy numbers for each candidate and for the ideal candidate:

$$\begin{aligned} \tilde{P}_i^{\Phi}(\alpha) &= \left\{c_{ij}, [c_{ij}^1(\alpha), c_{ij}^2(\alpha)],\ 1 \le j \le n\right\}, i = 1, 2, \ldots, R \\ \tilde{I}^{\Phi}(\alpha) &= \left\{(c_j, [I_j^1(\alpha), I_j^2(\alpha)]),\ 1 \le j \le n\right\} \end{aligned}$$

Step 4. For the chosen exigency level $\alpha \in [0,1]$, compare each candidate to the ideal candidate,

$$d_i(\alpha) = d(\tilde{P}_i^{\Phi}(\alpha), \tilde{I}^{\Phi}(\alpha)),\ 1 \le i \le R$$

Step 5. Order candidates for the exigency level α.

Step 6. Repeat steps 2, 3, 4, and 5 for different values of α.

Step 7. The company chooses the exigency level and selects the most suitable candidate.

5 Computational proof

In our example, we consider $n = 5$ competences, $k = 20$ candidates, $p = 4$ experts who valuate the candidates' competences and $q = 1$ expert (we are assuming that the firm has totally defined the requirements of the ideal candidate, the generalization to several experts for determining the ideal candidate would not have influence on the proposed method) who has valuated the ideal competences required for the job. We consider this number of candidates (20), because the managers confirmed us that these kind of tools are very useful when the number of applicants is high and they face up a duty of ranking them.

We will consider 11 values for α, $\alpha \in \{0, 0.1, 0.2, \ldots, 0.9, 1\}$.

5.1 Competences of the ideal candidate

The valuation of competences of the ideal candidate, given by the expert of the firm, is shown in table 1.

In this valuation the opinion of the experts about the competences of an ideal candidate not always gives the value 1 to the highest value. This would mean that the expert could consider not necessary for the candidate to have the highest performance in this competence.

5.2 Valuation of the competences of the candidates

The valuation given by each expert, about the competences of each candidate are shown in Tables 2, 3, 4 and 5.

	Low value	Highest value
Competence 1	0.65	0.70
Competence 2	0.80	1.00
Competence 3	0.50	0.80
Competence 4	0.80	0.85
Competence 5	0.50	0.90

Table 1: Valuation of the ideal candidate competences.

		Expert 1		Expert 2		Expert 3		Expert 4	
		L	H	L	H	L	H	L	H
Candidate 1	Comp. 1	0.3	0.65	0.3	0.8	0.35	0.8	0.7	1
	Comp. 2	0.2	0.7	0.7	0.9	0.4	0.6	0.35	0.6
	Comp. 3	0.35	0.5	0.5	0.7	0.25	0.9	0.4	0.8
	Comp. 4	0.4	0.8	0.5	0.6	0.35	0.9	0.25	0.65
	Comp. 5	0.15	0.55	0.5	0.6	0.35	0.9	0.25	0.65
Candidate 2	Comp. 1	0.25	0.6	0.25	0.7	0.4	0.8	0.35	0.7
	Comp. 2	0.35	0.8	0.35	0.6	0.3	0.6	0.7	0.8
	Comp. 3	0.4	0.6	0.4	0.5	0.7	0.8	0.35	0.7
	Comp. 4	0.45	0.75	0.5	0.8	0.35	0.8	0.4	0.6
	Comp. 5	0.5	0.7	0.5	0.8	0.35	0.8	0.4	0.6
Candidate 3	Comp. 1	0.25	0.7	0.35	0.7	0.3	0.55	0.5	0.9
	Comp. 2	0.35	0.65	0.3	0.6	0.4	0.7	0.2	0.7
	Comp. 3	0.3	0.55	0.5	0.9	0.6	0.85	0.35	0.65
	Comp. 4	0.4	0.9	0.6	0.85	0.25	0.7	0.35	0.6
	Comp. 5	0.55	0.75	0.5	0.7	0.35	0.6	0.3	0.65
Candidate 4	Comp. 1	0.6	0.8	0.5	0.7	0.4	0.6	0.7	0.7
	Comp. 2	0.7	0.9	0.8	1	0.9	0.95	0.8	1
	Comp. 3	0.35	0.8	0.6	0.9	0.5	0.8	0.7	0.7
	Comp. 4	0.75	0.8	0.85	0.85	0.8	0.8	0.8	0.85
	Comp. 5	0.5	0.9	0.6	0.8	0.7	0.7	0.5	0.8
Candidate 5	Comp. 1	0.25	0.6	0.25	0.7	0.4	0.8	0.35	0.7
	Comp. 2	0.35	0.8	0.35	0.6	0.3	0.5	0.7	0.8
	Comp. 3	0.3	0.7	0.4	0.5	0.7	0.8	0.35	0.7
	Comp. 4	0.5	0.6	0.5	0.8	0.02	0.7	0.3	0.6
	Comp. 5	0.6	0.65	0.5	0.8	0.2	0.8	0.3	0.6

Table 2: Valuation of the candidates 1–5.

		Expert 1		Expert 2		Expert 3		Expert 4	
		L	H	L	H	L	H	L	H
Candidate 6	Comp. 1	0.25	0.55	0.3	0.7	0.2	0.9	0.5	0.7
	Comp. 2	0.35	0.7	0.5	0.6	0.35	0.7	0.2	0.8
	Comp. 3	0.5	0.65	0.35	0.5	0.35	0.9	0.35	0.55
	Comp. 4	0.5	0.6	0.3	0.45	0.3	0.5	0.3	0.7
	Comp. 5	0.45	0.9	0.4	0.55	0.4	0.5	0.4	0.7
Candidate 7	Comp. 1	0.25	0.45	0.25	0.7	0.3	0.55	0.35	0.7
	Comp. 2	0.35	0.55	0.35	0.6	0.5	0.7	0.3	0.8
	Comp. 3	0.3	0.7	0.3	0.45	0.2	0.7	0.3	0.9
	Comp. 4	0.5	0.65	0.3	0.6	0.35	0.6	0.4	0.7
	Comp. 5	0.3	0.9	0.5	0.9	0.35	0.65	0.35	0.7
Candidate 8	Comp. 1	0.25	0.5	0.25	0.65	0.3	0.6	0.35	0.6
	Comp. 2	0.35	0.45	0.35	0.6	0.4	0.65	0.3	0.65
	Comp. 3	0.3	0.75	0.4	0.5	0.6	0.9	0.4	0.6
	Comp. 4	0.4	0.55	0.35	0.8	0.25	0.7	0.6	0.9
	Comp. 5	0.6	0.7	0.3	0.8	0.35	0.55	0.3	0.7
Candidate 9	Comp. 1	0.25	0.65	0.4	0.45	0.2	0.9	0.4	0.7
	Comp. 2	0.35	0.9	0.3	0.55	0.35	0.7	0.2	0.55
	Comp. 3	0.25	0.5	0.5	0.6	0.7	0.9	0.35	0.9
	Comp. 4	0.55	0.6	0.5	0.9	0.12	0.7	0.7	0.9
	Comp. 5	0.6	0.75	0.35	0.8	0.2	0.6	0.12	0.7
Candidate 10	Comp. 1	0.5	0.5	0.3	0.3	0.55	0.55	0.7	0.7
	Comp. 2	0.35	0.65	0.4	0.45	0.5	0.7	0.3	0.8
	Comp. 3	0.3	0.7	0.6	0.85	0.65	0.65	0.7	0.7
	Comp. 4	0.6	0.6	0.7	0.7	0.35	0.6	0.3	0.55
	Comp. 5	0.35	0.5	0.5	0.65	0.35	0.8	0.4	0.7
Candidate 11	Comp. 1	0.1	0.9	0.2	0.9	0.4	0.6	0.25	0.8
	Comp. 2	0.35	0.5	0.6	1	0.25	0.9	0.35	0.7
	Comp. 3	0.45	0.6	0.35	0.8	0.6	0.8	0.4	0.6
	Comp. 4	0.65	0.9	0.8	1	0.3	0.6	0.9	1
	Comp. 5	0.65	0.9	0.8	1	0.3	0.6	0.2	0.6
Candidate 12	Comp. 1	0.25	0.6	0.25	0.65	0.4	0.6	0.4	0.9
	Comp. 2	0.35	0.55	0.35	0.6	0.3	0.65	0.6	0.97
	Comp. 3	0.25	0.7	0.4	0.5	0.2	0.9	0.3	0.7
	Comp. 4	0.5	0.9	0.5	0.8	0.35	0.7	0.4	0.9
	Comp. 5	0.6	0.7	0.5	0.8	0.2	0.55	0.2	0.7

Table 3: Valuation of the candidates 6–11.

		Expert 1		Expert 2		Expert 3		Expert 4	
		L	H	L	H	L	H	L	H
Candidate 13	Comp. 1	0.25	0.55	0.25	0.45	0.4	0.9	0.35	0.9
	Comp. 2	0.35	0.7	0.3	0.6	0.3	0.7	0.7	0.9
	Comp. 3	0.35	0.65	0.5	0.9	0.5	0.9	0.22	0.7
	Comp. 4	0.5	0.9	0.35	0.65	0.3	0.5	0.2	0.6
	Comp. 5	0.4	0.5	0.3	0.8	0.25	0.7	0.3	0.55
Candidate 14	Comp. 1	0.4	0.55	0.4	0.7	0.35	0.6	0.5	0.7
	Comp. 2	0.35	0.7	0.6	0.65	0.2	0.7	0.3	0.7
	Comp. 3	0.3	0.9	0.4	0.45	0.35	0.65	0.4	0.9
	Comp. 4	0.4	0.5	0.5	0.55	0.6	0.65	0.35	0.7
	Comp. 5	0.6	0.65	0.5	0.7	0.25	0.8	0.3	0.6
Candidate 15	Comp. 1	0.25	0.6	0.25	0.65	0.35	0.55	0.4	0.65
	Comp. 2	0.35	0.8	0.35	0.6	0.3	0.7	0.6	0.9
	Comp. 3	0.35	0.7	0.3	0.5	0.5	0.6	0.25	0.7
	Comp. 4	0.5	0.55	0.5	0.8	0.04	0.75	0.35	0.9
	Comp. 5	0.45	0.7	0.6	0.65	0.2	0.65	0.3	0.7
Candidate 16	Comp. 1	0.25	0.65	0.25	0.9	0.2	0.6	0.4	0.7
	Comp. 2	0.35	0.9	0.35	0.45	0.35	0.65	0.7	0.9
	Comp. 3	0.2	0.5	0.4	0.55	0.7	0.75	0.06	0.7
	Comp. 4	0.5	0.6	0.5	0.7	0.3	0.6	0.2	0.6
	Comp. 5	0.6	0.65	0.5	0.65	0.5	0.55	0.3	0.9
Candidate 17	Comp. 1	0.1	0.9	0.2	0.9	0.4	0.6	0.25	0.8
	Comp. 2	0.35	0.5	0.6	1	0.25	0.9	0.35	0.7
	Comp. 3	0.4	0.6	0.35	0.8	0.6	0.8	0.4	0.6
	Comp. 4	0.55	0.85	0.8	0.95	0.3	0.6	0.8	1
	Comp. 5	0.65	0.85	0.8	0.95	0.3	0.6	0.2	0.6
Candidate 18	Comp. 1	0.25	0.5	0.6	0.7	0.6	0.75	0.4	0.9
	Comp. 2	0.35	0.8	0.35	0.65	0.25	0.7	0.6	0.7
	Comp. 3	0.25	0.7	0.4	0.6	0.35	0.6	0.25	0.6
	Comp. 4	0.5	0.6	0.5	0.9	0.04	0.6	0.35	0.65
	Comp. 5	0.6	0.9	0.3	0.8	0.2	0.8	0.2	0.9
Candidate 19	Comp. 1	0.25	0.55	0.3	0.7	0.2	0.9	0.5	0.7
	Comp. 2	0.35	0.9	0.35	0.45	0.35	0.65	0.7	0.9
	Comp. 3	0.35	0.7	0.3	0.5	0.5	0.6	0.25	0.7
	Comp. 4	0.4	0.5	0.5	0.55	0.6	0.65	0.35	0.7
	Comp. 5	0.5	0.9	0.5	0.9	0.5	0.9	0.5	0.9

Table 4: Valuation of the candidates 12–19.

		Expert 1		Expert 2		Expert 3		Expert 4	
		L	H	L	H	L	H	L	H
Candidate 20	Comp. 1	0.25	0.6	0.4	0.65	0.4	0.6	0.5	0.7
	Comp. 2	0.35	0.9	0.6	0.65	0.3	0.65	0.2	0.95
	Comp. 3	0.3	0.5	0.3	0.6	0.5	0.9	0.35	0.7
	Comp. 4	0.35	0.7	0.5	0.9	0.3	0.7	0.35	0.7
	Comp. 5	0.45	0.45	0.5	0.5	0.5	0.5	0.7	0.7

Table 5: Valuation of the candidate 20.

5.3 Solutions for various levels of exigency

We show the results obtained by columns in Table 6. Each one of them represents the candidates ordered from the best to the worst, and it is obtained for a given value of α, where $\alpha = 0, 0.1, 0.2, \ldots, 1$, respectivly.

	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
The best	4	4	4	4	4	4	4	4	4	4	4
	17	17	17	17	11	11	20	20	11	11	11
	19	11	11	11	17	17	11	11	20	20	17
	11	19	19	19	19	19	17	17	17	17	19
	6	6	6	6	6	6	19	19	19	19	20
	20	20	20	20	10	3	3	10	10	10	10
	2	2	2	2	2	10	10	3	3	3	3
	1	1	1	1	12	2	9	9	9	9	9
	12	12	12	12	3	12	6	2	2	2	13
	16	10	7	10	20	9	2	6	13	13	18
	10	7	10	3	1	1	1	12	5	5	2
	7	16	13	7	9	8	12	1	1	18	5
	13	13	16	8	8	7	14	5	12	1	1
	5	9	3	9	7	14	7	7	18	12	12
	9	5	9	13	14	20	5	14	6	7	7
	14	14	8	14	5	5	8	13	7	14	14
	8	3	5	5	13	13	13	18	14	8	8
	3	8	14	16	16	18	18	8	8	6	16
	18	18	18	18	18	16	16	16	16	16	6
The worst	15	15	15	15	15	15	15	15	15	15	15

Table 6: Selection of candidates using the Matching Level Index.

In Table 7 we show the results obtained using the Hamming distance.

	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
The best	4	4	4	4	4	4	4	4	4	4	4
	2	2	20	20	20	11	11	11	11	11	11
	19	20	2	2	2	20	17	17	17	17	17
	20	19	19	19	11	17	2	19	19	19	19
	10	10	10	10	19	2	20	2	2	2	2
	7	7	17	17	10	19	19	10	10	12	3
	12	17	11	11	17	10	10	20	12	10	12
	6	12	12	12	12	12	12	12	20	3	9
	17	11	7	7	14	14	14	3	3	9	18
	14	14	14	14	7	8	3	14	9	20	10
	11	6	8	8	8	7	1	9	14	14	14
	8	8	6	6	6	3	9	1	1	18	5
	13	13	13	13	1	1	8	13	18	1	20
	5	1	1	1	3	6	13	18	5	5	1
	16	5	5	3	13	13	7	5	13	13	13
	1	16	3	5	5	9	18	8	16	16	16
	15	15	16	16	9	5	5	7	8	15	15
	3	3	15	15	18	18	6	16	15	8	8
	18	18	18	18	15	16	16	6	7	7	7
The worst	9	9	9	9	16	15	15	15	6	6	6

Table 7: Selection of candidates using the Hamming distance.

6 Conclusions

Human Resources are considered an important source of competitive advantage in any company. One way companies can profit from these resources is through competence management.

From one side, the use of mathematical models in decision making provide some advantages as the obtaining of clear and quick solutions which are easy to understand. From the other side, the difficulties appear because, in general, mathematical models are objectives and quantify figures difficult to relate with this topics. To avoid these problems, we use Fuzzy Sets Theory which allows adding uncertainty and subjectivity to the problem. To represent accurately real life by a model is a hard work. The fuzzy logic does not add difficulty to traditional mathematics and it is closer to human thought. Fuzzy Theory allows avoiding the requirements of rigidity which could do a model not to make sense and it provides us with ignoring solutions that could be useful. In the personnel selection process an inflexible treatment of valuations of candidates can interfere with the ordering process because it does not consider all the necessary requirements. Also, a global valuation neutralizes positive valuation of competences with negative ones, being not fair. We propose a personnel selection model flexible and complementary, useful to order applicants to a post. Moreover, the use of intervals provides the expert with great flexibility to decide the suitable valuation in each case.

We emphasize in our practical case, as well as in any other, that it would be very risky to decide, not only the best candidate. But also an absolute and certain order of all candidates. Clearly, from the obtained results, the method point out the applicants more qualified and that less qualified. Our three preferred candidates would be P4, P11, and P20, and any one of them would be a good choice for the firm, but manager could add other specific requirements of the firm, outside of the method, to take the final decision. In the same way, the Human Resources Manager could add some specific conditions to decide the final order.

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