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A linguistic decision model for personnel management solved with a linguistic biobjective genetic algorithm

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Abstract

Staff selection for the varying activities performed by enterprises requires a coherent approach, which cannot be simplistic, to the information held. The use of flexible computation and the vague representation of knowledge available by means of linguistic labels allow the problem to be recognised as it is in real life. This paper is an attempt to supply a satisfactory solution to a real staff management problem with linguistic information presenting a linguistic decision model for personnel problem. For reaching a good solution, a novelty genetic algorithm with a linguistic biobjective fitness function is proposed.

Keywords: Staff selection; Relationships between jobs; Linguistic labels; Linguistic operators; Genetic algorithms

1. Introduction

The hiring of new staff and the assignment of current staff to specific tasks constitute a crucial decision, since the very survival of the enterprise can depend upon an appropriate choice being made. This is true in all areas of the economy, but is even more so in those in which turbulent trading conditions or cut-throat competition in the business make it vital to have personnel with sufficient flexibility and adaptability. In these circumstances correct choice of staff has a yet greater influence over future development of the company [23].

The aim of this paper is to attempt to devise a model for staff selection in conditions of uncertainty, such that it will both, reduce to a minimum the risks arising from performance of tasks by unsuitable personnel and maximise the capacity of the firm by means of optimal assignment of workers. This model will allow incorporation of all information which may be at hand, however ambiguous or subjective it may be, and cope with the lack of precision that is a concomitant of this sort of decision making process.

From the point of view of the business, the problem as described is essentially one of optimisation of one relationship: the efficiency of labour and the costs arising from its use. Nevertheless, no company, when choosing the best candidates for a post, can avoid the fact that workers interact with one another and do not perform their duties in isolation. This gives rise to the idea of forming teams able to carry out the work allocated, even if all their members are not of great ability or possessors of a range of skills.

In this respect, it is clear that personnel managers and others charged with determining the standards

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attained by each candidate in the skills needed for the job prefer to use natural language for this, whatever the tests used (aptitude tests, personality questionnaires, role-plays evaluation workshops, interviews and others). This is because it is fulfilled quite divorced from reality to express these standards in terms of strict numerical values [25]. Using normal language [31] may lead to the loss of the precision that numbers can give, but there is a positive counterpart in greater closeness to the problem.

In the light of the above comment, we present a linguistic [1] decision model that, according with the concept of fuzzy majority represented by the *linguistic weighted averaging* (LWA) operator [17] provides a linguistic valuation of the solutions of the staff management problem. Then, a selection process is necessary to obtain the best solution out of all available.

However, to optimise the assignment or selection process, there is a need for some tool able to grasp all the complexity which vague information brings with it, as is also the case if the decision-maker is to reach a good solution [20,21]. Thus, for the purposes of this paper we will use a genetic algorithm (GA) [3,18]. The reason for this is that it is a heuristic method of searching solutions and so does not impose restrictions upon the posing of a problem, however complex it may be. In this study, the algorithm is characterised by its use of a linguistic biobjective fitness function, which allows the evaluation of linguistic information. These two criteria are evaluated by means of the aforementioned linguistic decision model.

The paper is organised as follows. First, we introduce a short section about the linguistic approach to solve problems and some linguistic operators used in this paper. After that, in Section 3, we offer a descriptive analysis of the material aims of the work, the fuzzy-linguistic model for staff selection and the linguistic decision model for personnel management. Thereafter, the GA designed to achieve a good solution to the problem will be presented in Section 4. In Section 5, we will develop an example of the experimental work and discussion of the results obtained. The final section includes some concluding remarks.

[1] The word “linguistic” is related to the concept of “linguistic variables” in a formal way, and it does not imply some connections to linguistics.

2. Linguistic approach to solve problems

Normally, in a quantitative situation the information required is expressed as numerical values. However, when working in qualitative areas such as personnel management, which are characterised by vague or imprecise knowledge, the information cannot be set out in a precise numerical way. Thus, it would be a more realistic approach to use linguistic information instead of numbers, provided that the variables involved in the problem lend themselves to expression in this manner [31]. This way of looking at things can be applied to a wide range of problems, information retrieval [5], clinical diagnosis [6], education [19], and decision making [8,15,26,28].

A linguistic variable differs from a numerical one in that its values are not numbers, but words or sentences in a natural or artificial language. Since words, in general, are less precise than numbers, the concept of a linguistic variable serves the purpose of providing a means of approximated characterisation of phenomena, which are too complex, or too ill-defined to be amenable to their description in conventional quantitative terms.

Usually, depending on the problem domain, an appropriate linguistic term set is chosen and used to describe the vague or imprecise knowledge. The elements in the term set will determine the granularity of the uncertainty, that is the level of distinction among different counting of uncertainty. Bonissone and Decker studied the use of term sets with an odd cardinal, representing the mid term an assess of “approximately 0.5”, with the rest of the terms being placed symmetrically around it and the limit of granularity 11 or no more than 13 [4].

On the other hand, the semantic of the elements in the term set is given by fuzzy numbers defined on the $[0,1]$ interval, which are described by membership functions. Because the linguistic assessments are just approximate ones given by the individuals, we can consider that trapezoidal or triangular membership functions are good enough to capture the vagueness of those linguistic assessments, since it may be impossible or unnecessary to obtain more accurate values [9].

This paper supports the possibility of establishing in linguistic terms the information relating to the weighting of the skills needed. It would appear clear that a personnel management expert might not know in a

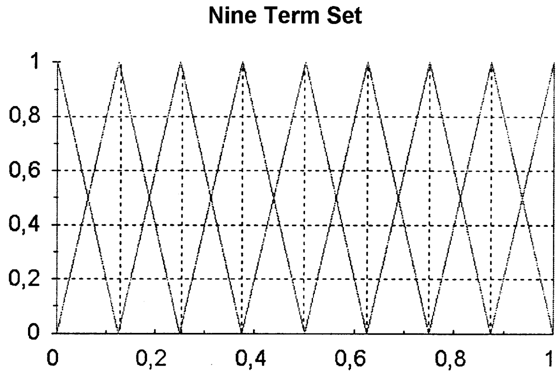

Fig. 1.

precise numerical way what the weighting for a skill is, but could indicate it in normal linguistic terms. To estimate weightings, and indeed other features, it has been chosen to use a set of nine linguistic labels as it is shown below in Fig. 1.

And the 4-tuples associated are

E	Essential (s_8)	$(0.875, 1, 1)$
VH	Very High (s_7)	$(0.75, 0.875, 0.1)$
FH	Fairly High (s_6)	$(0.625, 0.75, 0.875)$
H	High (s_5)	$(0.5, 0.625, 0.75)$
M	Moderate (s_4)	$(0.375, 0.5, 0.625)$
L	Low (s_3)	$(0.25, 0.375, 0.5)$
FL	Fairly Low (s_2)	$(0.125, 0.25, 0.375)$
VL	Very Low (s_1)	$(0, 0.125, 0.25)$
U	Unnecessary (s_0)	$(0, 0, 0.125)$

Accordingly, to establish what kind of label set to use ought to be the first priority. Then, let $S=\{s_i\},\ i\in H=\{0,\dots,T\}$ be a finite and totally ordered term set on $[0,1]$ in the usual sense [4,7]. Any label, s_i, represents a possible value for a linguistic variable, that is a vague property or constraint on $[0,1]$. We consider a term set, S, with its semantic given by linear triangular membership functions. Moreover, it must have the following characteristics:

1. the set is ordered: $s_i \geqslant s_j$ if $i \geqslant j$;
2. there is the negation operator: $Neg(s_i)=s_j$ such that $j=T-i$;
3. maximization operator: $Max(s_i,s_j)=s_i$ if $s_i \geqslant s_j$;
4. minimization operator: $Min(s_i,s_j)=s_i$ if $s_i \leqslant s_j$.

In the following, we analyse two ways to aggregate linguistic information and two linguistic operators used in this paper.

Firstly, we are going to analyse the information to be aggregated in a linguistic process. Clearly, there are two types of linguistic information:

1. *Non-weighted linguistic information*. This is the situation in which we have only one set of linguistic values to aggregate.
2. *Weighted linguistic information*. This is the situation in which we have a set of linguistic values to aggregate, for example opinions and each value is characterised by an importance degree, indicating its weight in the overall set of values.

In both cases, linguistic aggregation operators are needed that combine appropriately the information, in such a way, that the final aggregation is the "best" representation of the overall opinions. In the following subsections, we shall present the operators that we are going to consider in both cases.

2.1. *Non-weighted linguistic information*

In the literature various aggregation operators of linguistic information have been proposed. Some are based on the use of the associated membership functions of the labels [4,26], and others act by direct computation on labels [8,14,28–30]. Here we will use the later approach. We consider two operators, the linguistic ordered weighted averaging (LOWA) operator presented in [14] and the inverse-linguistic ordered weighted averaging (I-LOWA) operator presented in [17].

Definition (*Convex combination of m labels*; Delgado et al. [8]). Let $A=\{a_1,\dots,a_m\}$ be a set of labels to be aggregated, $\otimes$ the general product of a label by a positive real number and $\oplus$ the general addition of labels defined in [8]; then the convex combination operator of m labels, C^m, is defined as

$$C^m\{w_k,b_k,k=1,\dots,m\} = W\cdot B^{\mathrm{T}}$$
$$= w_1\otimes b_1 \oplus (1-w_1)\otimes C^{m-1}\{\beta_h,b_h,h=2,\dots,m\},$$

where $W=[w_1,\dots,w_m]$ is a weighting vector, such that (i) $w_i\in[0,1]$ and, (ii) $\sum w_i=1$. $\beta_h=w_h\big/\sum_2^m w_k$, $h=2,\dots,m$, and $B=\{b_1,\dots,b_m\}$ is a vector associated to A, such that

$$B=\sigma(A)=\{a_{\sigma(1)},\dots,a_{\sigma(n)}\},$$

where $a_{\sigma(j)}\leqslant a_{\sigma(i)} \forall i\leqslant j$, with σ being a permutation over the set of labels A.

Using the above definition, and the ordered weighted averaging (OWA) operator [27], in [14] was defined the LOWA operator.

Definition (LOWA *operator*)**.** Let $A=\{a_1,\dots,a_m\}$ be a set of labels to be aggregated, C^m the convex combination operator of m labels, $\otimes$ the general product of a label by a positive real number and $\oplus$ the general addition of labels defined in [8], then the LOWA operator, ϕ, is defined as

$$\phi(a_1,\dots,a_m)=C^m\{w_k,b_k,k=1,\dots,m\}.$$

If $m=2$, then C^2 is defined as

$$C^2\{w_i,b_i,i=1,2\}=w_1\otimes s_j\oplus(1-w_1)\otimes s_i$$
$$=s_k,s_j,s_i\in S \quad (j\geqslant i)$$

such that $k=min\{T,i+round(w_1\cdot(j-i))\}$, where "round" is the usual round operation, and $b_1=s_j$, $b_2=s_i$.

If $w_j=1$ and $w_i=0$ with $i\neq j\ \forall i$, then the convex combination is defined as

$$C^m\{w_i,b_i,i=1,\dots,m\}=b_j.$$

Definition (I-LOWA *operator*)**.** An I-LOWA (Inverse-Linguistic Ordered Weighted Averaging) operator, ϕ^I, is a type of LOWA operator, in which

$$B=\sigma^I(A)=\{a_{\sigma(1)},\dots,a_{\sigma(n)}\},$$

where $a_{\sigma(i)}\leqslant a_{\sigma(j)}\ \forall i\leqslant j$.

If $m=2$, then it is defined as

$$C^2\{w_i,b_i,i=1,2\}=w_1\otimes s_j\oplus(1-w_1)\otimes s_i$$
$$=s_k,s_j,s\in S \quad (j\leqslant i)$$

such that $k=min\{T,i+round(w_1\cdot(j-i))\}$.

Wide studies on these operators can be found in [16,17].

In the OWA operators the weights measure the importance of a value (in relation to other values) with independence of the information source. How to calculate the weighting vector of LOWA operator, W, is a basic question to be solved. A possible solution is that the weights represent the concept of fuzzy majority in the aggregation of LOWA operator using fuzzy linguistic quantifiers [32]. Yager proposed an interesting way to compute the weights of the OWA aggregation operator, which, in the case of a non-decreasing proportional fuzzy linguistic quantifier, Q, is given by the expression [27]

$$w_i=Q(i/n)-Q((i-1)/n),\quad i=1,\dots,n;$$

being the membership function of Q, as follows:

$$Q(r)=\begin{cases}0 & \text{if } r<a,\\ \dfrac{r-a}{b-a} & \text{if } a\leqslant r\leqslant b,\\ 1 & \text{if } r>b,\end{cases}$$

with $a,b,r\in[0,1]$. Some examples of non-decreasing proportional fuzzy linguistic quantifiers are "most" (0.3,0.8), "at least half" (0,0.5) and "as many as possible" (0.5,1). When a fuzzy linguistic quantifier, Q, is used to compute the weights of LOWA operator, ϕ, it is symbolised by ϕ_Q. Similarly for the I-LOWA operator, i.e., in this case it is symbolised by ϕ_Q^I.

Some examples of proportional quantifiers are shown in Fig. 2, where the parameters (a,b) are $(0.3,\ 0.8)$, $(0, 0.5)$ and $(0.\,5, 1)$, respectively.

2.2. Weighted linguistic information

We may find situations where the handle information is not equally important, that is managing weighted information. In order to aggregate weighted information, we have to combine linguistic information with the weights, which involves the transformation of the weighted information under the importance degrees.

According to these ideas, the linguistic weighted aggregation (LWA) operator to aggregate linguistic weighted information is provided in [17], which was defined using the LOWA operator [14], the concept of fuzzy majority represented by fuzzy linguistic quantifiers [31], and two families of linguistic connectives [17]. In the following we review it.

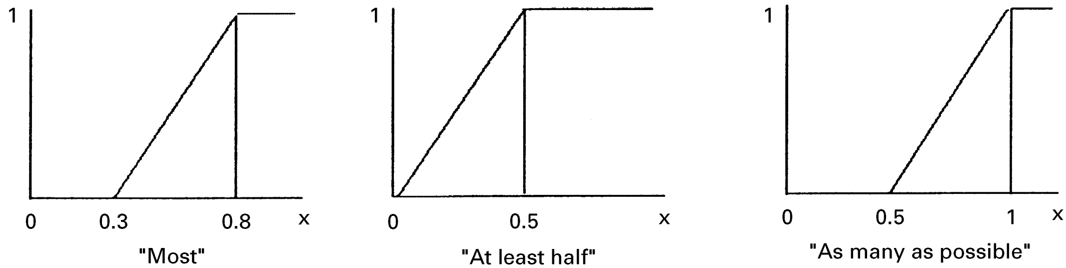

Fig. 2.

Before defining the LWA operator, let us present the following two families of linguistic connectives [17]:

(1) Linguistic conjunction functions $LC^{\rightarrow}$:

1. The classical MIN operator:

$$LC_1^{\rightarrow}(c,a) = MIN(c,a).$$

2. The nilpotent MIN operator:

$$LC_2^{\rightarrow}(c,a) = \begin{cases} MIN(c,a) & \text{if } c > Neg(a), \\ 0 & \text{otherwise.} \end{cases}$$

3. The weakest conjunction:

$$LC_3^{\rightarrow}(c,a) = \begin{cases} MIN(c,a) & \text{if } MAX(c,a) = S_T, \\ 0 & \text{otherwise.} \end{cases}$$

(2) Linguistic implication functions $LI^{\rightarrow}$:

1. Kleene–Dienes's implication function:

$$LI_1^{\rightarrow}(c,a) = MAX(Neg(c),a).$$

2. Gödel's implication function:

$$LI_2^{\rightarrow}(c,a) = \begin{cases} S_T & \text{if } c \leqslant a, \\ a & \text{otherwise.} \end{cases}$$

3. Fodor's implication function:

$$LI_3^{\rightarrow}(c,a) = \begin{cases} S_T & \text{if } c \leqslant a, \\ MAX(Neg(c),a) & \text{otherwise.} \end{cases}$$

Using these families of linguistic connectives as importance transformation functions that integrate the weights and the variables, the LWA operator handling as aggregation operators the LOWA or I-LOWA operators is defined. It is based on the combination of the LOWA and I-LOWA operators with several linguistic conjunction functions ($LC^{\rightarrow}$) and several linguistic implication functions ($LI^{\rightarrow}$), respectively.

Definition (*LWA operator*)**.** The aggregation of a set of weighted individual information, $\{(c_1,a_1),\ldots,(c_m,a_m)\}$, c_1 and a_1 being the weights and variable values respectively, the LWA operator is defined as

$$\begin{aligned} a_E &= LWA[(c_1,a_1),\ldots,(c_m,a_m)] \\ &= f[g(c_1,a_1),\ldots,g(c_m,a_m)], \end{aligned}$$

where $f \in \{\phi_Q, \phi_Q^I\}$ is an linguistic aggregation operator of transformed information and g is an importance transformation function, such that $g \in LC^{\rightarrow}$ if $f = \phi_Q$ and $g \in LI^{\rightarrow}$ if $f = \phi_Q^I$ with $LC^{\rightarrow} = \{LC_1^{\rightarrow}, LC_2^{\rightarrow}, LC_3^{\rightarrow}\}$ and $LI^{\rightarrow} = \{LI_1^{\rightarrow}, LI_2^{\rightarrow}, LI_3^{\rightarrow}\}$.

As it was commented in [17] when the aggregation operator, f, is the I-LOWA operator, ϕ_Q^I, and given that ϕ_Q^I is an aggregation operator with characteristics of a MIN-type aggregation operator, then we decide to use the linguistic implication functions, $LI^{\rightarrow}$, as the transformation function type. Something similar happens when f is the LOWA operator ϕ_Q. It can be observed that the LWA operator tries to reduce the effects of elements with low importance. To do so, when $f = \phi_Q$, the elements with low importance are transformed into small values and when $f = \phi_Q^I$ the elements with low importance are transformed into large values.

3. Linguistic decision model for personnel management

In this section we analyse the staff selection problem, the fuzzy linguistic model associated and propose the linguistic decision model for personnel management. This decision model will use the LOWA and I-LOWA operators representing the concept of fuzzy majority in order to aggregate the information available, and it provides us a method to evaluate linguistically the possible solutions of the problem.

3.1. Choice of staff

For the purposes of this paper, it will be assumed that the selection of staff consists of choosing a person for a job with a given profile, which may be defined by a set of measurements or values which can then be compared with any candidate's capacities.

In any case, by their nature, the schemes used in selecting staff are affected by a certain dose of subjectivity, and take the form of a succession of stages, during which candidates seen as less suitable are successively eliminated, while an attempt is simultaneously made to grasp what capacities those who are most suited to performing the tasks defining the job will have.

The phases to be completed as selection takes place may be summarised for guidance as follows [12,25]:

1. *Establishing a profile for the post*. This is done by means of an analysis of the tasks to be assigned and possible objectives to be attained. The profile also includes a list of the skills that the candidate must possess in order to carry out the activities involved in the job correctly, together with indications of the weight that each skill has in the specific post concerned.

In practice, it is usual to set up a list of all the necessary skills, with these being understood as meaning an essential characteristic of any individual who can do the work efficiently or better. This definition would include all the abilities, personal characteristics, motivations and other features such as self-image, social standing, knowledge the individual has, and so forth. Thus, the activities required by the job in question and the conditions under which duties must be performed may be scrutinised.

Traditionally, certain values have been used to fix the skills needed for a job. Nonetheless, it is obvious that for most of them the degree of compliance does not have to be rigid, and therefore modelling by means of normal linguistic variables can find an interesting application here.

Further, in establishing the post profile, it is necessary to include relationships with other staff, since organisations are not made up of people carrying out their work in isolation but rather interacting with one another. So, it may be more urgent to get a "good team" rather than "good individuals".

In addition, if it is a question of selecting staff for several posts, then those jobs which are of greatest importance to the management of the firm should be weighted in some manner, as these are the ones which should be most effectively matched to the ideal candidates.

2. *Candidate evaluation.* There is an extensive range of choices with respect to the tests that can be used (forms, interviews, examination, tests and so on). All try in one way or another to determine the level of aptitude of a person with respect to specific capacities that are deemed needful in order to perform the duties of a post correctly. However, it is also advisable to keep in mind not just the requirements for the post but also the conditions surrounding it, and especially those concerning the team of staff into which the holder must be incorporated.

It is during this phase that analysis of potential interactions between individuals comes into full play. The reason is that when tasks or jobs in which there is person-to-person contact or which are performed by teams are considered, it is essential to ensure that the workers involved cooperate, that is, that they are compatible when it comes to carrying out their joint work.

This justifies looking into the possible relationships between tasks, and into the level of compatibility between individuals, during the selection process. Such considerations are often made in a subjective way, so that the use of linguistic labels would allow greater closeness to the realities of the decision-making procedure being investigated.

3. *Match of candidates to profiles.* Once the degree to which each candidate has a given ability is established, this is compared with the capacities stated in the profiles set up for the jobs in question. This shows how far each candidates combination matches up to them, and allows an order of preference among these feasible solutions to be drawn up, though not without taking into account inter-personal compatibility,

which is an objective in parallel with the good match of candidates to posts.

3.2. Fuzzy-linguistic model for staff selection

The model proposed here consists of the following phases:

1. *Post and skills requirements.* Step 1 is to determine for what posts staff are to be recruited or to which posts existing staff are to be assigned:

$X = (X_1, X_2, \ldots, X_{m1}).$

Associated with each post we know the skill requirements and note the global set of skill requirement as

$Sk = (Sk_1, Sk_2, \ldots, Sk_{m2})$

together with the weighting that each requirement has for the various posts.

$$IC = \begin{pmatrix} IC_{11}, \ldots, IC_{1m2} \\ \vdots \qquad\qquad \vdots \\ IC_{m11}, \ldots, IC_{m1m2} \end{pmatrix}, \quad IC_{ij} \in W,$$

IC_{ij} being the importance level of the j skill for the i post. For the feature weighting, the labels that are proposed are the following:

$W = \{$*Essential*, *VeryHigh*, *Fairly High*, *High*, *Moderate*, *Low*, *Fairly Low*, *Very Low*, *Unnecessary*$\}$.

In addition, when staff are being selected for several posts, the expert or decision-maker may consider that not all of the positions have the same weighting, and prefer solutions aimed at putting the most suitable people into the most crucial posts. For this reason, a label associated with each position must be included to show the weighting that the position has for the recruitment procedure, which is under way. This characteristic is defined in this paper in exactly the same way as skill requirements, that is, with nine labels:

$IP = (IP_1, IP_2, \ldots, IP_{m1}), \quad IP_i \in W.$

Moreover, since the jobs are not independent of each other, the links between them should be analysed, as also the weighting of such links. Here, too, the use of nine labels is felt appropriate:

$$RP = \begin{pmatrix} -, RP_{12}, \ldots\ldots, RP_{1m1} \\ \vdots \qquad\qquad\qquad \vdots \\ RP_{m11}, \ldots, RP_{m1m1-1} - \end{pmatrix}, \quad RP_{ij} \in W,$$

RP_{ij} being the importance level of the relationship between the i and j posts.

2. *Candidates levels and relationships.* Once the posts have been characterised, the candidates are considered, $C = (C_1, C_2, \ldots, C_N)$. Information relating to them includes two types:

- the operational levels, which they demonstrate in the varying skills needed for the positions,

$$N = \begin{pmatrix} N_{11}, \ldots, N_{m2} \\ \vdots \qquad \vdots \\ N_{n1}, \ldots, N_{nm2} \end{pmatrix}, \quad N_{ij} \in LL$$

with the next set of labels associated:

$LL = \{$*Optimum*, *Very High*, *Fairly High*, *High*, *Moderate*, *Low*, *Fairly Low*, *Very Low*, *Lowest*$\}$.

- The relationships linking individuals with each other:

$$RC = \begin{pmatrix} -, RC_{12}, \ldots, RC_{1n} \\ \vdots \qquad\qquad \vdots \\ RC_{n1}, \ldots, RP_{nn-1}, - \end{pmatrix}, \quad RC_{ij} \in R$$

with the next set of labels associated:

$R = \{$*Excellent*, *Very Good*, *Fairly good*, *Good*, *Indifferent*, *Bad*, *Fairly Bad*, *Very Bad*, *Vile*$\}$.

Using this approach, it comes down to a problem of optimisation using imprecise information and having two aims or criteria:

- good levels in the skills needed for the posts on the candidates and
- good relationships among candidates for linked posts.

We will take into consideration these two criteria for designing the linguistic decision model.

Although we have described different term sets for each variable, in order to operate with them and taking into account that all of them have the same number of labels, only the first one will be considered. The other set of labels will be changed to this one from an operative point of view assuming a general label set. $L=\{l_0, l_1, \ldots, l_8\}$ and the corresponding transformation, for example l_3 is equivalent to *Bad*(R), *Low*(LL) *and* Low(W).

3.3. Linguistic decision model

Let $S=(S_1, S_2, \ldots, S_{m1})$ be a candidate solution obtained in some way, where $S_i \in \{1, 2, \ldots, N\}$, indicating the number associated to the order in the initial list of workers, and representing S_i the candidate C_{s_i} from C.

For evaluating the solutions we propose a model that uses the fuzzy information represented by linguistic labels. According with those aforementioned criteria, we follow the next steps:

Criterion 1. *Good level in the skills*

Step 1. First, to obtain a value of the candidate suitability on the skills of a post (S_i, X_i), we will apply an LWA operator as follows:

Step 1.1. For each post, X_i, there are $m2$ skills which define it, with $m2$ degrees of importance for each skill, IC_{ij}. Thus, to assess the suitability of the person S_i for each post a link must be established between the level that the person has of a given skill and the weight assigned to that skill for the job. To achieve this, the proposal is to use as importance transformation function the linguistic conjunction MIN that penalises solutions with individuals with a low level in important skills, denoting this function as $g_1(\cdot,\cdot)$:

$$g_1(IC_{ij}, N_{s,j}) = LC_1^{\rightarrow}(IC_{ij}, N_{s,j}) = Min(IC_{ij}, N_{s,j}), \quad j=1,\ldots,m_2.$$

Step 1.2. After that, to obtain a label representing the level of the individual in the post, we propose to use a LOWA with the "*most*" linguistic quantifier. Therefore the final label is

$$Z_{S_i} = f(g_1(IC_{i1}, N_{S_i1}), \ldots, g_1(IC_{im2}, N_{S_im2})) = \phi_Q(g_1(IC_{i1}, N_{S_i1}), \ldots, g_1(IC_{im2}, N_{S_im2})).$$

Step 2. Second, to obtain a value of the solution suitability on the skills of all the posts, we will apply again an LWA operator as follows:

Step 2.1. By taking the steps outlined above, it is possible to obtain a linguistic label setting a value on the ability of each candidate relative to each post. However, the intention is to give an overall value covering the suitability of candidates to posts that will include the fact that the various posts are themselves of different levels of importance. In view of this, it is proposed to use again as importance transformation function a classical conjunction MIN, so that the solution as to suitability for posts may be obtained in the form of a linguistic label. We denote this function as $g_2(\cdot,\cdot)$.

$$g_2(IP_i, Z_{S_i}) = LC_1^{\rightarrow}(IP_i, Z_{S_i}) = Min(IP_i, Z_{S_i}), \quad i=1,\ldots,m_1.$$

Step 2.2. Thus, to obtain a label representing the level of the overall solution, we propose to use a LOWA with the "*most*" linguistic quantifier.

$$Z_s = f(g_2(IP_1, Z_{S_1}), \ldots, g_2(IP_{m1}, Z_{S_{m1}})) = \phi_Q(g_2(IP_1, Z_{S_1}), \ldots, g_2(IP_{m1}, Z_{S_{m1}})).$$

With these steps, we have obtained a linguistic evaluation of the candidates in the skills of the post. Nevertheless, the goodness of the solutions will also be determined by the relationships between the candidates included in them. On the one hand, the connections between posts are known, as is the weighting for each, and on the other the relationships among candidates are known.

Criterion 2. *Good relationship among the candidates*

Step 1. First, to obtain a value of the candidate's relationships of each post, X_i, we will apply an LWA operator as follows:

Step 1.1. So, a link is established for each post between the weighting of its connections to other posts and the degree of relationship that the candidate allocated to the post has with candidates for related posts. To achieve this, the proposed method would be to use as importance transformation function the "Keene and Diene" Linguistic Implication. We denote this function as

$g_3(\cdot,\cdot)$:

$$g_3(RP_{ij}, RC_{S_iS_j}) = LI_1^{\rightarrow}(RP_{ij}, RC_{S_iS_j}) \\ = Max(Neg(RP_{ij}), RC_{S_iS_j}), \quad i = 1,\ldots,m_1.$$

Step 1.2. To obtain a label representing the relationship of the individuals of each post, v, we propose to use an I-LOWA operator with the "most" quantifier.

$$T_i = f(g_3(RP_{i1}, RC_{S_iS_1}),\ldots,g_3(RP_{im1}, RC_{S_iS_{m1}})) \\ = \phi_Q^I(g_3(RP_{i1}, RC_{S_iS_1}),\ldots,g_3(RP_{im1}, RC_{S_iS_{m1}})).$$

Step 2. Once this has been done, to set a value of the relationship to the overall solution, the proposal is to use an LOWA operator with the "most" quantifier.

$$T_S = f(T_1,\ldots,T_{m1}) = \phi_Q(T_1,\ldots,T_{m_1}).$$

With the last three steps, we have obtained a linguistic evaluation of the relationship among the candidates in the post.

Finally, we have obtained two linguistic labels (Z_s, T_s) that are the evaluation for each feasible solution, S, according to the two objectives of the problem: the level of the candidates on each post and the relationship among them.

In order to establish or select the best solution, next we propose, as selection process, to use a GA that presents a fitness function with two linguistic objectives.

4. A biobjective linguistic genetic algorithm

In this section, first we present a short introduction to GAs and after that, the proposal of the biobjective linguistic GA is introduced.

4.1. Genetic algorithms

GAs are general-purpose search algorithms which use principles inspired by natural genetics to evolve solutions to problems [18]. The basic idea is to maintain a population of chromosomes, which represents candidate solutions to the concrete problem being solved, which evolves over time through a process of competition and controlled variation. Each chromosome in the population has an associated *fitness* to determine (*selection*) which chromosomes are used to form new ones in the competition process. The new ones are created using genetic operators such as *crossover* and *mutation*. GAs have had a great measure of success in search and optimisation problems. The reason for a great part of this success is their ability to exploit the information accumulated about an initially unknown search space in order to bias subsequent searches into useful subspaces, i.e., *their adaptation*. This is their key feature, particularly in large, complex, and poorly understood search spaces, where classical search tools (enumerative, heuristic, ...) are inappropriate, offering a valid approach to problems requiring efficient and effective search techniques.

A GA starts off with a population of randomly generated *chromosomes*, and advances toward better *chromosomes* by applying genetic operators modelled on the genetic processes occurring in nature. The population undergoes evolution in a form of natural selection. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and on the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators such as crossover and mutation. An *evaluation or fitness* function must be devised for each problem to be solved. Given a particular chromosome, a possible solution, the fitness function returns a single numerical fitness, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome.

Although there are many possible variants of the basic GA, the fundamental underlying mechanism consists of three operations:

1. evaluation of individual fitness,
2. formation of a gene pool (intermediate population) through selection mechanism, and
3. recombination through crossover and mutation operators.

Fig. 3 shows the structure of a basic GA, where $P(t)$ denotes the population at generation t.

GAs may deal successfully with a wide range of problem areas, particularly in management applications [31]. The main reasons for this success are: (1) GAs can solve hard problems quickly and reliably, (2) GAs are easy to interface to existing simulations

```
Procedure Genetic Algorithm
Begin (1)
      t=0;
      initialise P(t);
      evaluate P(t);
      While ( Not termination-condition) do
      Begin (2)
                      t=t+1;
                      select P(t) from P(t-1);
                      recombine P(t);
                      evaluate P(t);
      end (2)
end (1)
```

Fig. 3.

and models, (3) GAs are extendible and (4) GAs are easy to hybridise. All these reasons may be summed up in to only one: GAs are robust. GAs are more powerful in difficult environments where the space is usually large, discontinuous, complex and poorly understood. They are not guaranteed to find the global optimum solution to a problem, but they are generally good at finding acceptably good solutions to problems quickly. These reasons have been behind the fact that, during the last few years, GA applications have grown enormously in many fields.

It is generally accepted that the application of a GA to solve a problem must take into account the following five components:

1. A genetic representation of solutions to the problem,
2. a way to create an initial population of solutions,
3. an evaluation function which gives the fitness of each chromosome,
4. genetic operators that alter the genetic composition of offspring during reproduction, and
5. values for the parameters that the GA uses (population size, probabilities of applying genetic operators, etc.).

The basic principles of GAs were first laid down rigorously by Holland [18], and are well described in many books, such as [13,22].

4.2. *Linguistic biobjectives in genetic algorithms*

In this paper, the GA that we are going to propose will use the ordered codification of the solutions. Chains of candidates are generated of the same size as the number of posts available. Two types of problems are distinguished:

- *assignment*, in which the number of posts is the same as the number of candidates, and
- *selection*, in which the number of candidates is greater than the number of posts.

An example of a solution for a case of five posts with five candidates available to fill them (assignment) would be

$$S=(2,4,1,3,5).$$

This solution indicates that candidate no. 2 comes in the first place and is assigned the first job, no. 4 comes in second place and gets the second job, no. 1 gets job 3, no. 3 gets job 4 and no. 5 gets job 5.

Once the coding has been decided upon, random processes generate a battery of these solutions.

4.2.1. *Fitness function*

To establish the fitness of each solution to the problem, we propose to use the linguistic decision model proposed in the last section. Doing it we obtain two labels that indicate the goodness of each solution.

4.2.2. *Parents selection*

To classify the solutions we propose to establish according to an expert the goals or levels required for both the objectives of the problem and then compare the solutions among them and the goals looking for one or some of them that are dominated for none [10,11].

Let $Y_i=(Y_{i1},Y_{i2})$ be a vector of labels associated with the solution i, and $\alpha=(\alpha_1,\alpha_2)$ the goals established for an expert to each criterion. We define the dominance concept between two solution evaluating vectors according to the following expression:

$$\begin{aligned} &i \textit{ Dominate to } j \Leftrightarrow (Y_{i1} > Y_{j1} \textit{ and } Y_{i2}\geqslant Y_{j2}) \textit{ or}\\ &\quad (Y_{i1}\geqslant Y_{j1} \textit{ and } Y_{i2}>Y_{j2}) \textit{ or}\\ &\quad (Y_{i1}\geqslant \alpha_1 \textit{ and } Y_{i2}<\alpha_2 \textit{ and } Y_{i2}>Y_{j2}) \textit{ or}\\ &\quad (Y_{i2}\geqslant \alpha_2 \textit{ and } Y_{i1}<\alpha_1 \textit{ and } Y_{i1}>Y_{j1}).\end{aligned}$$

So we can obtain for every chromosome the number of others that dominate it.

Let N be the number of individuals of the population. Each one, i, is dominated for t_i individuals. We call those values as the rank associated with chromosomes. According to these ranks, we can establish classes of individuals with the same rank. We denote by $C=\{C_0,\dots,C_H\}$ the set of classes, ordered by the rank value, r_j being the number of individuals in the class C_j. Then, we order the individuals, according to the rank and therefore, the first r_0 chromosomes belong to the first class and so on. Due to this, the individuals belonging to the class C_j have $\sum_{k=0}^{j-1} s_k$ individuals before them.

After that, we apply a linear ranking [2] to obtain the selection probabilities:

$$P_i = \frac{1}{N}\left(\eta_{\max} - (\eta_{\max} - \eta_{\min})\frac{i-1}{N-1}\right)$$

where $\eta_{\max}$ and $\eta_{\min}$ are the expected number of copies for the best or worst solution, respectively, being $\eta_{\min} \in [0,1]$ and $\eta_{\max} = 2 - \eta_{\min}$, and N the number of solutions. This method averages the selection probabilities of individuals with equal rank (of the same class), so that, all of them are sampled with the same rate.

4.2.3. Crossover

According to the two mentioned possibilities we use two variants:

- *Assignment problems*: We propose to use the Partially-Mapped Crossover (PMX) [13] which complies with the need for the solutions generated by it to continue to be feasible responses to the problem.
- *Selection problems*: We propose to use the special uniform crossover designed to keep the solutions resulting as feasible ones. The steps are as follows:
  1. At the beginning of the crossover process we have two “parents”. For example, in a problem of eight candidates to be assigned to five posts the solutions could be

     $S_1 = (8,3,4,6,1)$,
     $S_2 = (6,2,4,5,7)$.
  2. First, we keep the repeated candidates and those that are in these posts on the other solutions in the offspring. Thus, we obtain

     $S_1' = (8,\ ,4,6,\ )$,
     $S_2' = (6,\ ,4,5,\ )$.
  3. Second, we assign random uniformly the remaining candidates to the offspring. Two resulting solutions could be

     $S_1' = (8,2,4,6,1)$,
     $S_1' = (6,3,4,5,7)$.
  4. Finally, after the crossover process, we have obtained two solutions that are feasible to the problem.

4.2.4. Mutation

In the same way we consider the two possibilities:

- *Assignment problems*: The mutation proposed is the exchange mutation between two posts of the solution [1]. An example could be

  $S_1 = (2,4,5,3,1)$,
  $S_1' = (2,3,5,4,1)$.
- *Selection problems*: We propose to use two different mutations, one like the previous type and the other that introduces individuals not contained in the solution, for example,

  $S_1 = (2,4,5,7,9)$,
  $S_1' = (2,1,5,7,9)$.

  and for their application we select one of them randomly.

4.2.5. Halt criteria for the best solution search

The proposal is to execute the algorithm a number of generations specified by the user. Moreover, in order not to lose good solutions, the characteristic termed elitism [13] has been introduced. This procedure consists of keeping the best individual from a population in successive generations unless and until some other individual succeeds in doing better with respect to fitness. In this way, the best solution for a previous population is not lost until outclassed by a more fitting solution.

5. Experiment: an example of a practical application

In this section we present an example that deals with the choice of staff for a branch office of a banking institution. To do that we divide this section into subsections according to three steps as follows: linguistic model, decision process and GA-based selection.

5.1. Introduction to the problem: Linguistic model

Assume that a banking firm wishes to open a new branch. The first step is to determine which posts are

Table 1

IC_{ij}	POST 1	POST 2	POST 3	POST 4	POST 5
Directing	Essential	–	–	–	–
Authorising/delegating	Fairly High	–	–	–	–
Integrity	Moderate	–	–	–	–
Fixing objectives	High	–	–	–	–
Strategic vision	Fairly High	–	–	–	–
Collecting information	–	Low	Very High	–	–
Analysing problems	–	High	–	–	–
Checking on procedures	–	Fairly High	–	–	–
Multitasking	–	Very High	Fairly Low	–	–
Knowledge of organisation	–	Moderate	–	–	–
Mathematical ability	–	Moderate	–	Fairly High	–
Team work	–	–	Moderate	–	Moderate
Flexibility	–	–	High	–	Fairly Low
Specialisation	–	–	Fairly High	–	–
Commercial orientation	–	–	–	Moderate	Very High
Personal charm	–	–	–	Low	Fairly High
Spoken communication	–	–	–	High	–
Customer orientation	–	–	–	Fairly High	Very High

Table 2

RP_{ij}	POST 1	POST 2	POST 3	POST 4	POST 5
POST 1	–	Fairly High	High	Moderate	Fairly Low
POST 2	Fairly High	–	Moderate	Moderate	Low
POST 3	Low	Very High	–	Very High	High
POST 4	Low	Moderate	Very High	–	Very High
POST 5	Fairly Low	Moderate	Fairly High	Very High	–

to be filled, and what status in terms of urgency each is to have in relation to the selection process. Thus, we might have:

Post number	**Name**	**Status** (IP_j)
1	Branch manager	Essential
2	Supervisor	Fairly High
3	Administrative Officer	Moderate
4	Administrative Clerk	Low
5	Counter clerk/teller	Very Low

For each post, owing to a number of studies, the skills which must be developed and the weighting that each has for the position in question are known, as is shown in Table 1.

In addition, the last piece of information needed in setting up these posts would be the relationships between each post and the others and the importance set on such relationships, as is shown in Table 2.

Once the posts involved in the selection procedure have been determined, the candidates must next be considered. Assume that there are 11 people who might be able to take on the jobs arising in the new branch.

Candidate	**Name**
1	C.1
2	C.2
3	C.3
4	C.4
5	C.5
6	C.6
7	C.7
8	C.8
9	C.9
10	C.10
11	C.11

Table 3

N_{ij}	C.1	C.2	C.3	C.4	C.5	C.6	C.7	C.8	C.9	C.10	C.11
Directing	Low	Fairly Low	High	High	High	Low	Low	Moderate	Very High	Low	Very Low
Authorising	Low	Fairly Low	Moderate	Fairly High	Fairly High	Moderate	Moderate	High	Very High	Low	Moderate
Team work	Moderate	Low	Low	Fairly Low	Low	Very High	Very High	Fairly High	Very Low	Optimum	Very Low
Flexibility	High	Low	Moderate	Low	Fairly High	Very High	Very High	Moderate	Very Low	Optimum	Fairly Low
Integrity	High	Low	High	Moderate	Fairly Low	Fairly High	Moderate	Fairly High	Very High	Moderate	Very Low
Collecting information	Low	Moderate	Moderate	Fairly Low	Lowest	Very High	Very High	Lowest	Moderate	Fairly Low	Moderate
Analysing problems	Low	Fairly Low	Moderate	High	Moderate	Fairly High	High	Very High	Fairly High	High	Very Low
Fixing objectives	Low	Low	Moderate	High	Fairly Low	Very High	Fairly High	Fairly High	Moderate	High	Moderate
Checking on procedures	High	High	Low	Moderate	Very Low	Fairly High	High	Low	Fairly High	Moderate	Very Low
Multitasking	Moderate	High	Moderate	Fairly High	Low	Very High	Very High	Fairly High	Moderate	Low	Moderate
Knowledge of the organisation	Low	Moderate	Moderate	Moderate	Very Low	Moderate	Low	Fairly Low	Moderate	Moderate	Moderate
Strategic version	Fairly Low	Fairly Low	Low	High	Lowest	High	Fairly Low	Very High	Very High	Very Low	Very Low
Specialisation	Moderate	Moderate	Moderate	Fairly Low	Lowest	Very High	Very High	Lowest	Moderate	Fairly Low	Moderate
Commercial orientation	Lowest	Low	Low	Very High	High	Moderate	Moderate	Moderate	Fairly High	Very High	Very Low
Personal charm	Very Low	Moderate	Moderate	Very High	Fairly High	Very High	Lowest	Low	Moderate	Very High	Moderate
Spoken communication	Fairly Low	Low	Fairly Low	Very High	Fairly Low	High	Moderate	Low	Fairly High	Moderate	Very Low
Customer orientation	Moderate	Moderate	Moderate	Very High	High	Fairly High	Fairly Low	Very Low	Moderate	Very High	Moderate
Mathematical ability	Fairly Low	Fairly Low	High	Very High	Very High	Very High	Lowest	High	High	Low	Very Low

For each one it is necessary to find out by some appropriate means the levels in each of the skills required for the posts, as shown in Table 3.

Finally, as there are links between the posts, the candidates must be looked at in order to find out the relationships that there would be between them, as shown in Table 4.

5.2. Linguistic decision model

Let $S=(\mathrm{C.1},\mathrm{C.2},\mathrm{C.3},\mathrm{C.4},\mathrm{C.5})$ be a possible solution. We are going to apply the decision model on it for obtaining the linguistic evaluation associated to the criteria.

Criterion 1. *Good level in the skills*

Step 1.1. (see Table 5)

Step 1.2.

$$Z_{S_1}=\phi_Q(M,L,L,L,FL)=[0,0.4,0.4,0.2,0]$$
$$(M,L,L,L,FL)=L,$$

$$Z_{S_2}=\phi_Q(H,H,M,L,FL,FL)$$
$$=[0,0.2\widehat{6},0.\widehat{3},0.\widehat{3},0.0\widehat{6},0]$$
$$(H,H,M,L,FL,FL)=M,$$

$$Z_{S_3}=\phi_Q(M,M,M,L,FL)$$
$$=[0,0.4,0.4,0.2,0](M,M,M,L,FL)=L,$$

$$Z_{S_4}=\phi_Q(FH,H,M,L,FL)=[0,0.4,0.4,0.2,0]$$
$$(FH,H,M,L,FL)=M,$$

$$Z_{S_5}=\phi_Q(FH,H,H,L,FL)=[0,0.4,0.4,0.2,0]$$
$$(FH,H,H,L,FL)=M.$$

Step 2.1. (see Table 6)

Step 2.2.

$$Z_S=\phi_Q(M,L,L,L,VL)=[0,0.4,0.4,0.2,0]$$
$$(M,L,L,L,VL)=L.$$

With these steps above, we have obtained a linguistic evaluation (*Low*) of the solution candidates in the skills of the post.

Criterion 2. *Good relationship among the candidates*

Step 1.1. (see Table 7)

Step 1.2.

$$T_1=\phi_Q^I(FH,L,M,FL)=[0.1,0.5,0.4,0]$$
$$(FH,L,M,FL)=L,$$
$$T_2=\phi_Q^I(M,L,L,VL)=[0.1,0.5,0.4,0]$$
$$(M,L,L,VL)=L,$$
$$T_3=\phi_Q^I(FH,H,L,L)=[0.1,0.5,0.4,0]$$
$$(FH,H,L,L)=M,$$
$$T_4=\phi_Q^I(M,M,L,L)=[0.1,0.5,0.4,0]$$
$$(M,M,L,L)=M,$$
$$T_5=\phi_Q^I(H,M,L,FL)=[0.1,0.5,0.4,0]$$
$$(H,M,L,FL)=L.$$

Step 2.

$$T_S=\phi_Q(M,M,L,L,L)=[0,0.4,0.4,0.2,0]$$
$$(M,M,L,L,L)=L.$$

With the last three steps, we have obtained a linguistic evaluation (*Low*) for the relationship among the solution candidates in the post.

Therefore, we have obtained two labels for evaluating the solution S, (*Low*, *Low*).

5.3. Linguistic biobjective genetic algorithm

In this subsection we show the GA based selection process of this example. So, for the purposes of application of the operational model, the parameters used in finding the solution by means of the model proposed were

- Number of generations: 25
- Number of individuals: 20
- Crossover probability: 60%
- Mutation probability: 40%
- Skill goal: Fairly High (L6)
- Relationship goal: Fairly Good (L6)

It should be pointed out that the use of a high mutation probability was motivated by the need to bring new individuals into the chains, since if this were not so all that would be obtained would be the best combination of those initially considered who got past the first selections.

Table 4

RC_{ij}	C.1	C.2	C.3	C.4	C.5	C.6	C.7	C.8	C.9	C.10	C.11
C.1	–	Very Good	Bad	Good	Moderate	Very Bad	Moderate	Fairly Bad	Vile	Indifferent	Fairly Bad
C.2	Very Bad	–	Bad	Moderate	Moderate	Good	Moderate	Very Bad	Very Bad	Indifferent	Very Bad
C.3	Very Good	Fairly Good	–	Bad	Good	Moderate	Good	Bad	Good	Indifferent	Very Bad
C.4	Very Bad	Good	Moderate	–	Bad	Good	Moderate	Moderate	Very Bad	Good	Very Good
C.5	Very Good	Good	Good	Bad	–	Good	Fairly Bad	Very Bad	Vile	Indifferent	Very Bad
C.6	Very Good	Good	Moderate	Bad	Good	–	Moderate	Bad	Good	Very Good	Very Good
C.7	Bad	Good	Good	Fairly Good	Very Good	Fairly Good	–	Fairly Bad	Very Bad	Very Good	Fairly Good
C.8	Bad	Fairly Good	Good	Very Good	Moderate	Fairly Good	Moderate	–	Very Bad	Good	Good
C.9	Good	Fairly Good	Fairly Good	Good	Indifferent	Good	Fairly Good	Good	–	Indifferent	Indifferent
C.10	Fairly Bad	Good	Indifferent	Fairly Good	Bad	Good	Indifferent	Indifferent	Very Bad	–	Fairly Good
C.11	Fairly Bad	Bad	Fairly Bad	Fairly Bad	Fairly	Indifferent	Vile	Indifferent	Fairly Bad	Bad	–

Table 5

Post 1	Directing	Authorising	Integrity	Fixing object.	Strategic vision
IC_{ij}	Essential	Fairly High	Moderate	High	Fairly High
$N_{S_i j}$	Low	Low	High	Low	Fairly Low
$LC_1^{\rightarrow}$	Low	Low	Moderate	Low	Fairly Low

Post 2	Collect. inf.	Anal. problems	Checking proc.	Multitasking	Know. organ.	Math. ability
IC_{ij}	Low	High	Fairly High	Very High	Moderate	Moderate
$N_{S_i j}$	Moderate	Fairly Low	High	High	Moderate	Fairly Low
$LC_1^{\rightarrow}$	Low	Fairly Low	High	High	Moderate	Fairly Low

Post 3	Collect. inf.	Multitasking	Team work	Flexibility	Specialisation
IC_{ij}	Very High	Fairly High	Moderate	High	Fairly High
$N_{S_i j}$	Moderate	Moderate	Low	Moderate	Moderate
$LC_1^{\rightarrow}$	Moderate	Fairly Low	Low	Moderate	Moderate

Post 4	Math. ability	Commerc. or.	Personal charm	Spoken com.	Customer or.
IC_{ij}	Fairly High	Moderate	Low	High	Fairly High
$N_{S_i j}$	Very High	Very High	Very High	Very High	Very High
$LC_1^{\rightarrow}$	Fairly High	Moderate	Low	High	Fairly High

Post 5	Team work	Flexibility	Commerc. or.	Personal charm	Customer or.
IC_{ij}	Moderate	Fairly Low	Very High	Fairly High	Very High
$N_{S_i j}$	Low	Fairly High	High	Fairly High	High
$LC_1^{\rightarrow}$	Low	Fairly Low	High	Fairly High	High

Table 6

S	Post 1	Post 2	Post 3	Post 4	Post 5
IP_i	Essential	Fairly High	Moderate	Low	Very Low
Z_{S_i}	Low	Moderate	Low	Moderate	Moderate
$LC_1^{\rightarrow}$	Low	Moderate	Low	Low	Very Low

Table 7

Post 1	1	2	3	4	5
RP_{ij}	–	Fairly High	High	Moderate	Fairly Low
$RC_{S_i S_j}$	–	Very High	Low	High	Moderate
$LI_1^{\rightarrow}$	–	Fairly High	Low	Moderate	Fairly Low

Post 2	1	2	3	4	5
RP_{ij}	Fairly High	–	Moderate	Moderate	Low
$RC_{S_i S_j}$	Very Low	–	Low	Moderate	Moderate
$LI_1^{\rightarrow}$	Very Low	–	Low	Moderate	Low

Post 3	1	2	3	4	5
RP_{ij}	Low	Very High	–	Very High	High
$RC_{S_i S_j}$	Very low	Fairly High	–	Low	High
$LI_1^{\rightarrow}$	Very Low	Fairly High	–	Low	High

Table 7 (continued)

Post 4	1	2	3	4	5
RP_{ij}	Low	Moderate	Very High	–	Very High
$RC_{S_iS_j}$	Very Low	High	Moderate	–	Low
$LI_1^{\rightarrow}$	Low	Moderate	Moderate	–	Low

Post 5	1	2	3	4	5
RP_{ij}	Fairly Low	Moderate	Fairly High	Very High	–
$RC_{S_iS_j}$	Very high	High	High	Low	–
$LI_1^{\rightarrow}$	Fairly Low	Moderate	High	Low	–

The graphics of the evolution of the best individual in each generation according to the goals is displayed in Figs. 4 and 5.

This graphic shows that the relationship goal was fulfilled for the best individual of the first generation but the skill goal not until half of the generations.

In the practical example analysed the final solution obtained was (Skill: Excellent; Relationship: Very Good):

Post name	**Candidate**
Branch manager	C.9
Supervisor	C.6
Administrative officer	C.7
Administrative clerk	C.4
Counter clerk/teller	C.11

With this example, we have shown the running of the genetic selection process with the linguistic bicriteria based on the linguistic decision model.

6. Concluding remarks

The results obtained from this work fall into two clusters. The first consists of the linguistic formulation of a staff selection model that could be adapted to the problem under consideration. The second has to do with the establishment of a specific procedure to solve it. This is based on a linguistic decision model that is used as an evaluation tool of the linguistic bicriteria GA-based selection process.

In this way, an attempt is made to demonstrate the usefulness that the model being proposed in this paper could have for real problems from the business world.

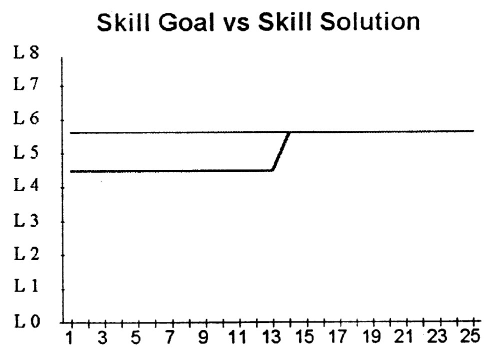

Fig. 4.

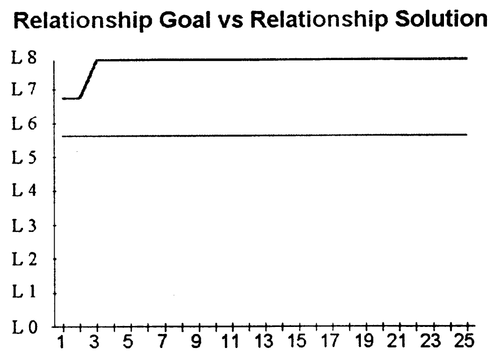

Fig. 5.

Finally, to point out that the linguistic formulation for personnel management is very general and it can be adopted without doubts to different problems under the same consideration.

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