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 is proposed a novelty genetic algorithm with a linguistic biobjective fitness function.

KEY WORDS: 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 [Pfeffer, 1995].

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 to 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 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 [Strauss and Sayles, 1981]. Using normal language [Zadeh, 1975] 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 above comment, we present a linguistic decision model that, according with the concept of fuzzy majority represented by the Linguistic Weighted Averaging (LWA) operator, provides a linguistic valuation of the solutions of the staff management problem. Then, a selection process is necessary to obtain the best solution of the 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 [López-González et al., 1995; López-González et al., 1997]. Thus, for the purposes of this paper we will use a genetic algorithm (GA) [Holland, 1975]. 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 bijective 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.

### 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 [Zadeh, 1975]. This way of looking at things can be applied to a wide range of problems, information retrieval [Bordogna and Passi, 1993], clinical diagnosis [Degani and Bortolan, 1988], education [Law, 1996], decision making [Tong and Bonissone, 1980; Yager, 1992a; Delgado et al., 1983b; Herrera et al., 1995; ...].

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 [Bonissone and Decker, 1986].

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 linear trapezoidal 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. This representation is achieved by the 4-tuple \((a_i, b_i, \alpha_i, \beta_i)\), the first two parameters indicate the interval in which the membership value is 1; the third and fourth parameters indicate the left and right width. Formally speaking, it seems difficult to
accept that all individuals should agree on the same membership function associated to linguistic terms, and therefore, there are not any universality distribution concepts.

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 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 [Bonissone and Decker, 1986]. A graphical example is shown in Figure 1.

![Figure 1](image)

And the 4-tuples associated are:

- **E** Essential: (1, 1, 0, 0)
- **VH** Very High: (.98, .99, .05, .01)
- **FH** Fairly High: (.78, .92, .06, .05)
- **H** High: (.63, .80, .05, .06)
- **M** Moderate: (.41, .58, .09, .07)
- **L** Low: (.22, .36, .05, .06)
- **FL** Fairly Low: (.1, .18, .06, .05)
- **VL** Very Low: (.01, .02, .01, .05)
- **U** Unnecessary: (0, 0, 0, 0)

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 [Bonissone and Decker, 1986; Tong, 1980], and others act by direct computation on labels [Delgado et al., 1993b; Herrera and Verdegay, 1993; Yager 1992a; Yager 1992b; Yager, 1995]. Here we will use the later approach. We
consider two operators, the linguistic ordered weighted averaging (LOWA) operator presented in [Herrera and Verdegay, 1993] and the inverse-linguistic ordered weighted averaging (I-LOWA) operator presented in [Herrera and Herrera-Viedma, 1997].

**Definition of the LOWA operator.** Let $A = \{a_1, \ldots, a_m\}$ be a set of labels to be aggregated, then the LOWA operator, $\phi$, is defined as

$$
\phi(a_1, \ldots, a_m) = W \cdot B^T = C^m \{w_k, b_k, k = 1, \ldots, m\} = w_1 \otimes b_1 \otimes (1 - w_1) \otimes C^{m-1} \{\beta_h, b_h, h = 2, \ldots, m\}
$$

where $W = [w_1, \ldots, w_m]$, is a weighting vector, such that: (i) $w_i \in [0, 1]$ and, (ii) $\sum w_i = 1$.

$\beta_h = w_h / \sum^m w_k$, $h = 2, \ldots, m$, and $B = \{b_1, \ldots, b_m\}$ is a vector associated to $A$, such that,

$$B = \sigma(A) = \{a_{\sigma(1)}, \ldots, a_{\sigma(m)}\}$$

where, $a_{\sigma(j)} \leq a_{\sigma(i)} \forall i \leq j$, with $\sigma$ being a permutation over the set of labels $A$. $C^m$ is the convex combination operator of $m$ labels, $\otimes$ is the general product of a label by a positive real number and $\oplus$ is the general addition of labels defined in [Delgado et al., 1993b].

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

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

such that $k = \min\{T, i + \text{round}(w_i \cdot (j - i))\}$, 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:

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

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

$$B = \sigma^I(A) = \{a_{\sigma(1)}, \ldots, a_{\sigma(m)}\}$$

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

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

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

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

The LOWA and I-LOWA operators are increasing monotonous, commutative, "around" operators, which verify the axioms: Unrestricted domain, Unanimity or Idempotence, Positive association of social and individual values, Independence of irrelevant alternatives, Citizen sovereignty, Neutrality [Herrera et al., 1996].

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 [Zadeh, 1983]. 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 this expression [Yager, 1988]:
\[ w_i = Q(i/n) - Q((i-1)/n), \quad i = 1, \ldots, n; \]

being the membership function of \( Q \), as follows:

\[ Q(r) = \begin{cases} 
0 & \text{if } r < a \\
\frac{r - a}{b - a} & \text{if } a \leq r \leq b \\
1 & \text{if } r > b 
\end{cases} \]

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, \( \Phi \), it is symbolised by \( \Phi_Q \). Similarly happens for the I-LOWA operator, i.e., in this case it is symbolised by \( \Phi^I_Q \).

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

![Figure 2](image)

### 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 [Herrera and Herrera-Viedma, 1997], which was defined using the LOWA operator [Herrera and Verdegay, 1993], the concept of fuzzy majority represented by a fuzzy linguistic quantifiers [Zadeh, 1983], and two families of linguistic connectives [Herrera and Herrera-Viedma, 1997]. In the following we review it.

**Definition of the LWA operator.** The aggregation of set of weighted individual opinions, \( \{c_1, a_i\}, \ldots, \{c_m, a_m\} \) , according to the LWA operator is defined as

\[ (c_E, a_E) = \text{LWA}[(c_1, a_i), \ldots, (c_m, a_m)], \]

where the importance degree of the opinion of the group, \( c_E \), is obtained as

\[ c_E = \Phi_Q(c_1, \ldots, c_m). \]
and, the opinion of the group, \(a_E\), is obtained as

\[a_E = f \left[ g(c_1, a_1), \ldots, g(c_m, a_m) \right],\]

where \(f \in \{ \phi_Q, \phi_Q^l \}\) is an linguistic aggregation operator of transformed information and \(g\) is an importance transformation function, such that \(g \in LC\) if \(f = \phi_Q\) and \(g \in LI\) if \(f = \phi_Q^l\), being \(LC\) the following linguistic conjunction functions:

1. The classical MIN operator:
   \[LC_1^{-}(c, a) = \text{MIN}(c, a)\]

2. The nilpotent MIN operator:
   \[LC_2^{-}(c, a) = \begin{cases} \text{MIN}(c, a) & \text{if } c > \text{Neg}(a) \\ 0 & \text{otherwise} \end{cases}\]

3. The weakest conjunction:
   \[LC_3^{-}(c, a) = \begin{cases} \text{MIN}(c, a) & \text{if } \text{MAX}(c, a) = s_T \\ 0 & \text{otherwise} \end{cases}\]

and \(LI\) any of the following linguistic implication:

1. Kleene-Dienes's implication function:
   \[LI_1^{-}(c, a) = \text{MAX}(\text{Neg}(c), a)\]

2. Godel's implication function:
   \[LI_2^{-}(c, a) = \begin{cases} s & \text{if } c \leq a \\ a & \text{otherwise} \end{cases}\]

3. Fodor's implication function:
   \[LI_3^{-}(c, a) = \begin{cases} s & \text{if } c \leq a \\ \text{MAX}(\text{Neg}(c), a) & \text{otherwise} \end{cases}\]

Where "MAX" stands for maximum operator and "MIN" stands for minimum operator.

It should be observed that LWA operator tries to reduce the effect of elements with low importance. In order to do so, when \(f = \phi_Q\), the elements with low importance are transformed into small values and when \(f = \phi_Q^l\) into large ones.

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 the three following [Strauss and Sayles, 1981; Gil-Aluja, 1996]:

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 in respect of 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 in respect of 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 co-operate, 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 to 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 one is to determine for what posts staff are to be recruited or to which posts existing staff are to be assigned.

      \[ X^* = \{ X_1^*, X_2^*, \ldots, X_m^* \} \]

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

      \[ S_k = \{ S_{k1}, S_{k2}, \ldots, S_{km} \} \]

      together with the weighting that each requirement has for the various posts.
For the feature weighting, the labels that are proposed are the following:

\[ W = \{ \text{Essential, Very High, Fairly High, High, Moderate, Low, Fairly Low, Very Low, Unnecessary} \} \]

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.

\[ IP = \{ IP_1, IP_2, \ldots, IP_n \} \], \( IP_i \in W \)

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

\[ RP = \{ -, RP_{12}, \ldots, RP_{1m} \} \], \( RP_{ij} \in W \)

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, 
  \[ N = \{ N_1, \ldots, N_m \} \], \( N_{ij} \in LL \)

with the next set of labels associated:

\[ LL = \{ \text{Optimum, Very High, Fairly High, High, Moderate, Low, Fairly Low, Very Low, Lowest} \} \]

- and the relationships linking individuals with one another:
  \[ RC = \{ -, RC_{12}, \ldots, RC_{1n} \} \], \( RC_{ij} \in R \)

with the next set of labels associated:

\[ R = \{ \text{Excellent, Very Good, Fairly good, Good, Indifferent, Bad, Fairly Bad, Very Bad, Vile} \} \]

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 in 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 their and taking into account that all of them have the same number of labels, only the first one will be considered. The others set of labels will be changed to this one from an operative point of view assuming a general label set. \( L = \{ l_0, l_1, \ldots, l_k \} \) and the corresponding transformation, for example \( l_3 \) is equivalent to \textit{Bad (R)}, \textit{Low (LL)} and \textit{Low (W)}.

### 3.3 Linguistic Decision Model

Let \( S = \{ S_1, S_2, \ldots, S_m \} \) be a candidate solution obtained in some way, where \( S_i \in \{ 1, 2, \ldots, N \} \).

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 \( m_2 \) skills which define it, with \( m_2 \) degrees of importance for each skill, \( IC_{ij} \). Thus, to assess the suitability of the person \( S_j \) 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 the linguistic conjunction MIN that penalises solutions with individuals with a low level in important skills.

\[
g_1(IC_{ij}, N_{S_j}) = LC_1^\leftarrow (IC_{ij}, N_{S_j}), j = 1, \ldots, m_2
\]

- **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:

\[
Z_{S_j} = f (g_1(IC_{ij}, N_{S_j}), \ldots, g_1(IC_{im_2}, N_{S_{im_2}})) = \phi (g_1(IC_{ij}, N_{S_j}), \ldots, g_1(IC_{im_2}, N_{S_{im_2}}))
\]

- **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 a classical conjunction MIN, so that the solution as to suitability for posts may be obtained in the form of a linguistic label.

\[
g_2(IP_{i1}, Z_{S_j}) = LC_1^\rightarrow (IP_{i1}, Z_{S_j}), i = 1, \ldots, m_1
\]

- **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.

\[
Z_{S} = f (g_2(IP_{i1}, Z_{S_j}), \ldots, g_2(IP_{m1}, Z_{S_{m1}})) = \phi (g_2(IP_{i1}, Z_{S_j}), \ldots, g_2(IP_{m1}, Z_{S_{m1}}))
\]

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 candidates’ relationships of each post, \( X'_i \), we will apply a 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 the “Keene and Diene” Linguistic Implication.

\[
g_3(RP_{i,j}, RC_{s,b}) = LI_{1}^{-1}(RP_{i,j}, RC_{s,b}), i = 1, \ldots, m
\]

• **Step 1.2.** To obtain a label representing the relationship of the individuals of each post, \(X'\), we propose to use an I-LOWA operator with the “most” quantifier.

\[
T_i = f(g_3(RP_{i,1}, RC_{s,b}), \ldots, g_3(RP_{i,m}, RC_{s,b})) = \phi_\bigg(g_3(RP_{i,1}, RC_{s,b}), \ldots, g_3(RP_{i,m}, RC_{s,b}))
\]

• **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.

\[
T_S = f(T_1, \ldots, T_m) = \phi_\bigg(T_1, \ldots, T_m
\]

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 \((Z_i, T_i)\), 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 [Holland, 1975]. 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.
Figure 3 shows the structure of a basic GA, where $P(t)$ denotes the population at generation $t$.

### 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)

Figure 3

GAs may deal successfully with a wide range of problem areas, particularly in management applications [Bietthahn and Nissen, 1995]. 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 and models, 3) GAs are extendible and 4) GAs are easy to hybridise. All these reasons may be summed up in 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 [Holland, 1975], and are well described in many books, such as [Goldberg, 1989; Michalewicz, 1992].

### 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:

$$S_1 = \{2, 4, 1, 3, 5\}$$

This solution indicates that candidate n. 2 comes in the first place and is assigned the first job, n. 4 comes in second place and gets the second job, n. 1 gets job 3, n. 3 gets job 4 and n. 5 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 indicates 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 of objectives of the problem and then compare the solutions among them and the goals looking for one o some of them that are dominated for none [Fonseca and Fleming, 1993; Fonseca and Fleming, 1995].

Let \( Y_i = \{Y_{i1}, Y_{i2}\} \) a vector of labels associated with the solution \( i \), and \( \alpha = \{\alpha_1, \alpha_2\} \) the goals established for an expert. The following expression show the concept of dominance:

\[
\begin{align*}
&i \text{ Dominate to } j \iff \\
&\begin{cases}
(Y_{i1} > Y_{j1} \text{ and } Y_{i2} \geq Y_{j2}) \text{ or } (Y_{i1} \geq Y_{j1} \text{ and } Y_{i2} > Y_{j2}) \\
Y_{i1} \geq \alpha_1 \text{ and } Y_{i2} < \alpha_2 \text{ and } Y_{i2} > Y_{j2} \\
Y_{i2} \geq \alpha_2 \text{ and } Y_{i1} < \alpha_1 \text{ and } Y_{i1} > Y_{j1}
\end{cases}
\end{align*}
\]

So we can obtain for every chromosome the number of other ones 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 \( C = \{C_0, \ldots, C_N\} \) the set of classes, ordered by the rank value, being \( s_j \) the number of individuals in the class \( C_j \). Then, we order the individuals, according to the rank and therefore, the first \( s_0 \) chromosomes belong to the first class and so on. Due to this, the individuals belonging to the class \( C_j \) have \( \sum_{k=0}^{i-1} s_k \) individuals before them.

After that, we apply a linear ranking [Baker, 1985] to obtain the selection probabilities:

\[
P_i = \frac{1}{N} \left( \eta_{\text{max}} - (\eta_{\text{max}} - \eta_{\text{max}}) \frac{i-1}{N-1} \right)
\]

and we average the selection probabilities of individuals with equal rank (of the same class). So that, all of them be sampled with the same rate.

4.2.3 Crossover

According with the two mentioned possibilities we use two variants:

- **Assignment problems**: we propose to use the Partially-Mapped-Crossover (PMX) [Goldberg, 1989] 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:
     \[
     S'_1 = \{8, 3, 4, 6, \} \\
     S'_2 = \{6, 4, 5, \}
     \]
3. Second, we assign random uniformly the remaining candidates to the offspring. Two resulting solutions could be:
   \[ S_1' = \{8, 2, 4, 6, 1\} \]
   \[ S_2' = \{6, 3, 4, 5, 7\} \]

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 post of the solution [Banzhaf, 1990]. 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 mutation, one like the previous type and 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 until the best solution is found. Moreover, in order not to lose good solutions, the characteristic termed elitism [Goldberg, 1989] 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 in respect of fitness. In this way, the best solution for a previous population is not lost until outclassed by a more fitting solution.

As explained, application of the model proposed here allows a staff selection process to be carried out under conditions of uncertainty. It takes into account possible links between jobs and the cooperation or lack of it that would ensue among staff members involved. As a form of summary, Figure 4 lays out indications of all the steps described above.
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 in subsections according to three steps as follows: linguistic model, decision process and GA based selection.

5.1 Introduction to the problem: Linguistic model

Let it be imagined that a banking firm wishes to open a new branch. The first step is to determine which posts are 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) |
|-------------|-----------------------|-------------|
| 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, thanks 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 Chart 1:

| IC_i         | 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 |

Chart 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 Chart 2.
Once the posts involved in the selection procedure have been determined, the candidates must next be considered. Let it be imagined that there are eleven people who might be able to take on the jobs arising in the new branch.

| Candidate Name | POST 1   | POST 2   | POST 3   | POST 4   | POST 5   |
|----------------|----------|----------|----------|----------|----------|
| 1              | Fairly High | High     | Moderate | Fairly Low |         |
| 2              | Fairly High | -        | Moderate | Moderate | Low      |
| 3              | Low       | Very High| -        | Very High | High     |
| 4              | Low       | Moderate | Very High| -        | Very High|
| 5              | Fairly Low| Moderate | Fairly High | Very High | -        |

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 Chart 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 Chart 4.

| Candidate Name | POST 1   | POST 2   | POST 3   | POST 4   | POST 5   |
|----------------|----------|----------|----------|----------|----------|
| C. 1           | -        | Very Good| Bad      | Good     | Moderately Very Bad | Moderately Fairly Low | Vile | Indifferent | Fairly Bad |
| C. 2           | Very Bad | -        | Bad      | Moderate | Moderate | Good | Moderately Very Bad | Very Bad | Indifferent | Very Bad |
| C. 3           | Very Good| Fairly Good | - | Bad | Good | Moderately Good | Bad | Good | Indifferent | Very Bad |
| C. 4           | Very Bad | Good | Moderate | - | Bad | Good | Moderately Moderate | Very Bad | Vile | Indifferent | Very Bad |
| C. 5           | Very Good| Good | Bad | - | Good | Moderately Good | Bad | Good | Very Good | Very Good |
| C. 6           | Very Good| Good | Moderate | Bad | Good | - | Moderately Good | Bad | Good | Very Good | Very Good |
| C. 7           | Bad | 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 | Modera | - | Very bad | Good | Good |
| C. 9           | Good | Fairly Good | Good | Indifferent | Good | Fairly Good | Good | - | Indifferent | Indifferent |
| C.10           | Fairly Bad | Good | Indifferent | Fairly good | Bad | Good | Indifferent | Very bad | - | Fairly Good |
| C.11           | Fairly Bad | Bad | Fairly Bad | Fairly Bad | Indifferent | Vile | Indifferent | Fairly bad | - |
| \(N_{ij}\) | 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| 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 Vision| 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 |

**Chart 3**
5.2 Linguistic decision model

Let $S={C.1, C.2, C.3, C.4, C.5}$ 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.**

| Post 1 | Collect. Inf. | Anal. Problems | Checking Proc. | Multitasking | Know. Organ. | Math. Ability |
|--------|---------------|----------------|----------------|--------------|--------------|---------------|
| $IC_{ij}$ | Low | High | Fairly high | Very High | Moderate | Moderate |
| $N_{sj}$ | Moderate | Fairly Low | High | High | Moderate | Fairly Low |
| $LC_{ij}^+$ | Low | Fairly Low | High | High | Moderate | 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 |
| $N_{sj}$ | Moderate | Fairly Low | High | High | Moderate | Fairly Low |
| $LC_{ij}^+$ | Low | Fairly Low | High | High | Moderate | Fairly Low |

- **Step 1.2.**

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

$$Z_{S_2} = \phi_Q\left(H, H, M, L, FL, FL\right) = [0, 0.26, 0.3, 0.06, 0] \cdot (H, H, M, L, FL, FL) = M$$

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

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

$$Z_{S_5} = \phi_Q\left(FH, H, H, L, FL\right) = [0.0, 0.4, 0.4, 0.2, 0] \cdot (FH, H, H, L, FL) = M$$

- **Step 2.1.**

| S | Post 1 | Post 2 | Post 3 | Post 4 | Post 5 |
|---|-------|-------|-------|-------|-------|
| $IP_{ij}$ | Essential | Fairly High | Moderate | Low | Very Low |
| $Z_{S_1}$ | Low | Moderate | Low | Moderate | Moderate |
| $LC_{ij}^+$ | Low | Moderate | Low | Low | Very Low |
• Step 2.2.

\[ Z_s = \phi_Q(M, L, L, VL) = [0, 0.4, 0.4, 0.2, 0] \]

With this steps above, we have obtain a linguistic evaluation \((Low)\) of the solution candidates in the skills of the post.

**Criterion 2. Good relationship among the candidates.**

• Step 1.1.

| Post 1 | 1     | 2      | 3     | 4     | 5     |
|--------|-------|--------|-------|-------|-------|
| \(RP_{ij}\)  | -     | Fairly High | High  | Moderate | Fairly Low |
| \(RC_{,ij}^{,s}\)  | -     | Very High  | Low   | High   | Moderate |
| \(LI_i^{+}\)  | -     | Fairly High | Low   | Moderate | Fairly Low |

| Post 2 | 1     | 2      | 3     | 4     | 5     |
|--------|-------|--------|-------|-------|-------|
| \(RP_{ij}\)  | Fairly High | -     | Moderate | Moderate | Low   |
| \(RC_{,ij}^{,s}\)  | Very Low | -     | Low   | Moderate | Moderate |
| \(LI_i^{+}\)  | Very Low | -     | Low   | Moderate | Low   |

| Post 3 | 1     | 2      | 3     | 4     | 5     |
|--------|-------|--------|-------|-------|-------|
| \(RP_{ij}\)  | Low   | Very High | -     | Very High | High   |
| \(RC_{,ij}^{,s}\)  | Very low | Fairly High | -     | Low   | High   |
| \(LI_i^{+}\)  | Very Low | Fairly High | -     | Low   | High   |

| Post 4 | 1     | 2      | 3     | 4     | 5     |
|--------|-------|--------|-------|-------|-------|
| \(RP_{ij}\)  | Low   | Moderate | Very High | -     | Very High |
| \(RC_{,ij}^{,s}\)  | Very Low | High   | Moderate | -     | Low   |
| \(LI_i^{+}\)  | Low   | Moderate | Moderate | -     | Low   |

| Post 5 | 1     | 2      | 3     | 4     | 5     |
|--------|-------|--------|-------|-------|-------|
| \(RP_{ij}\)  | Fairly Low | Moderate | Fairly High | Very High | -     |
| \(RC_{,ij}^{,s}\)  | Very high | High   | High   | Low   | -     |
| \(LI_i^{+}\)  | Fairly Low | Moderate | High   | Low   | -     |

• Step 1.2.

\[ T_1 = \phi_Q^i(FH, L, M, FL) = [0.1, 0.5, 0.4, 0] (FH, L, M, FL) = L \]

\[ T_2 = \phi_Q^i(M, L, VL) = [0.1, 0.5, 0.4, 0] (M, L, VL) = L \]

\[ T_3 = \phi_Q^i(FH, H, L, L) = [0.1, 0.5, 0.4, 0] (FH, H, L, L) = M \]

\[ T_4 = \phi_Q^i(M, M, L, L) = [0.1, 0.5, 0.4, 0] (M, M, L, L) = M \]

\[ T_5 = \phi_Q^i(H, M, L, FL) = [0.1, 0.5, 0.4, 0] (H, M, L, FL) = L \]
• Step 2.

\[ T_S = \phi_0 (M, M, L, L, L) = [0, 0.4, 0.4, 0.2, 0] (M, M, L, L, L) = L \]

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

Therefore, we have obtained two labels for evaluating the solution \(S\), \((\text{Low}, \text{Low})\).

### 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.

The graphic of the evolution of the best individual in each generation according to the goals is displayed in Figure 5.

![Figure 5](image)

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

On the other hand the elitist individual graphic is shown in Figure 6. In this one can be observed that there are two improvements in the GA generations before the convergence, proving that the algorithm has had a well behaviour. The graphic shows the representation of the index of the labels.
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.

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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