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Design and Development of a Genetic Algorithm Based on Fuzzy Inference Systems for Personnel Assignment Problem

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Abstract

In today's competitive markets, the role of human resources as a sustainable competitive advantage is undeniable. Reliable hiring decisions for personnel assignation contribute greatly to a firms' success. This is especially relevant in disasters management and emergency situations where times plays a fundamental role for effective relief and the cost-benefit ratio can be improved. The Personnel Assignment Problem (PAP) relies on assigning the right people to the right positions. The solution to the PAP provided in this paper includes the introducing and testing of an algorithm based on a combination of a Fuzzy Inference System (FIS) and a Genetic Algorithm (GA). The evaluation of candidates is based on subjective knowledge and is influenced by uncertainty. A FIS is applied to model experts' qualitative knowledge and reasoning. Also, a GA is applied for assigning assessed candidates to job vacancies based on their competency and the significance of each position. The proposed algorithm is applied in an Iranian company in the chocolate industry. Thirty-five candidates were evaluated and assigned to three different positions. The results were assessed by ten Human Resources (HR) managers and the algorithm results proved to be satisfactory in discovering desirable solutions. Also, two GA selection techniques (tournament selection and proportional roulette wheel selection) were applied and compared. Results show that tournament selection has better performance than proportional roulette wheel selection.

Keywords: *Fuzzy Inference Systems, Genetic Algorithm, Personnel Assignment Problem, Disasters Management and Emergencies, Cost-benefit ratio*

Managerial Relevance Statement

The process of hiring and candidate evaluation is blended with uncertainty. Determining candidates' competency is not exact in nature and is based on experts' qualitative knowledge. Also, putting best candidates to the most proper job vacancies based on their competency and position importance, is a kind of imprecise issue. In addition, for disaster and emergency situations in which decisions need to be made under time pressure, solutions to gain time for human resources assignment to increase relief to specific zones and vulnerable collectives are especially necessary (Altay & Green, 2006). In this paper, we capture the uncertainty of the experts' qualitative knowledge and reasoning by means of FISs. Besides, a GA is applied to obtain optimal or near optimal solution for assigning right people to the right positions.

To sum up, the contribution of this paper is to find a solution for PAP by handling uncertainty using FISs and optimizing the solution applying a GA. The results are assessed by experts and desirable solutions are obtained.

Introduction

The concept of globalization has deeply changed the traditional market dynamics. Companies spread their markets based on competitive advantages, while others face aggressive competitors when trying to adapt to rapidly changing environments. So, for all the companies that intend to survive in today's markets, establishing and maintaining a sustainable competitive advantage based on expertise and competition becomes a crucial need.

According to Barney (1991), a firm preserves a sustainable competitive advantage provided that it benefits from resources which are valuable, rare, non-imitable, non-substitutable and non-transferable. Human resources are a source of sustainable competitive advantage for the firm according to those characteristics. There is growing evidence indicating that individuals' varied skills and knowledge lead to the creation of economic value in firms (Marvel, Davis, & Sproul, 2016). Overall, Human Resource Management (HRM) practices positively affect organizational performance (Boselie, Dietz, & Boon, 2005; Buller & McEvoy, 2012; Combs, Liu, Hall, & Ketchen, 2006; Jogaratnam, 2017; Katou & Budhwar, 2010; Minguela-Rata & Arias-Aranda, 2009), as well as competitiveness and efficiency (Lopez□Cabrales, Valle, & Herrero, 2006). In fact, as Zhao and Du (2012) discussed, human resources contribute greatly to the success of enterprises and should be given top priority. Regarding natural disasters, these cause many life losses as well as countless damages all over the world. So, implementing a fast, efficient and effective system for personnel assigments to guarantee relief to save human lives is of vital importance.

Therefore, in competitive markets as well as in emergency situations, staffing is vital to a firm's development. Assigning the right people to the right positions leads to positive organizational outcomes such as reducing the employee turnover rate, improving productivity, improving the cost-benefit ratio and increasing customer satisfaction (Yu, Zhang, & Xu, 2013). However, poor hiring decisions impose significant costs related to engaging, training and dismissing inadequate employees (Golec & Kahya, 2007). The strategic implementation of PAP can provide an effective solution to the aforementioned problems. PAP entails personnel assignment considering candidates' abilities to job positions considering the restrictions of available human resources and positions in a way that an optimal solution can be obtained (Dunnette, 1966). The major specifications of PAP are as follows: The number of job positions is smaller than the number of candidates; all positions should be occupied by the candidates; each candidate should be matched only with one position; and finally, the assignment process should guarantee that the total profit is maximized or the total cost is minimized (Herrera, López, Mendana, & Rodríguez, 1999; S.-Y. Lin et al., 2010).

In the literature, PAP has a wide range of applications in assigning the adequate people to the right positions. Nurses (Errarhout, Kharraja, & Corbier, 2016) or therapists assignment (M. Lin, Chin, Wang, & Tsui, 2016) to patients in home health care; agents assignments to factory lines (Hougaard, Moreno-Ternero, & Østerdal, 2014) or workers assignment to specific business units in Waste and Recycling Services (Niknafs, 2016) are some examples as well as reviewers' assignments (Daş & Göçken, 2014) or military personnel assignment (Korkmaz, Gökçen, & Çetinyokuş, 2008) among others.

In general, since the evaluation of candidates in the assignment process is measured across different metrics, PAP is basically a Multi Criteria Decision Making (MCDM) problem. Various approaches are used in dealing with the personnel selection problem in the literature. Herrera et al. (1999) evaluated the personnel by means of verbal information in a fuzzy environment. Then, a GA was applied to solve the staff selection problem. S.-Y. Lin et al. (2012) combined the particle swarm optimization (PSO) algorithm with the random-key (RK) encoding scheme in order to deal with a bi-objective personnel assignment problem (BOPAP). H.-T. Lin (2010) combined analytic network process (ANP) with fuzzy data envelopment analysis (DEA) to solve the personnel selection problem. Other PAP approaches involve the application of a robust optimization approach (Guillaume, Houé, & Grabot, 2014), the Fuzzy Analytic Hierarchy Process (FAHP) model (Güngör, Serhadlıoğlu, & Kesen, 2009), the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model (Boran, Genç, & Akay, 2011; Sang, Liu, & Qin, 2015), the fuzzy AHP-TOPSIS model (Kusumawardani & Agintiara, 2015), the Group decision making under hesitant fuzzy environment (Yu et al., 2013) or the MCDM technique (Dursun & Karsak, 2010; Vecchione, Alessandri, & Barbaranelli, 2012).

Among the studies that applied fuzzy logic in personnel selection, Canós and Liern (2008) based on available information, presented two models for personnel selection by means of fuzzy sets. Their models simulate evaluation of experts by using Ordered Weighted Average (OWA). In order to deal with the vagueness in personnel selection, Ali, Nikolić, and Zahra (2017) proposed a model based on fuzzy MCDM. They applied FAHP for personnel evaluation. Mediouni and Cheikhrouhou (2019) presented a methodology for expert selection in the field of humanitarian and social projects under the uncertainty where FAHP was applied to assess the candidates and TOPSIS was used to rank them.

The present approach to solve PAP involves two phases:

1. Evaluation. The competency approach to assigning candidates to job positions is defined as the ability to carry out the defined tasks in an effective way (Różewski & Małachowski, 2009). However, the usual evaluations of candidate competencies (especially facing some vague criteria in nature such as team working abilities or attention to detail) are based on subjective knowledge and influenced by uncertainty. This is where using a FIS is a suitable approach. In the case of dealing with uncertain numerical data, linguistic data or imprecise data, FIS has the capability of modeling human qualitative knowledge and reasoning, which is useful in formulating expert knowledge and reasoning system in a formal mathematical model. By doing this, the presence of experts for evaluating candidates would be unnecessary since the mentioned FIS is able to fulfil the process of reasoning based on expert knowledge. To the best of our knowledge, there is a lack of studies combining FIS and GA to handle PAP.

2. Optimization. In this phase, we apply the GA which is inspired by natural genetics in order to solve problems (Herrera, López, Mendaña, & Rodríguez, 2001). GAs are general-purpose search algorithms successfully designed to deal with multi-objective optimization problems (Toroslu & Arslanoglu, 2007). In our case, a set of best candidates evaluated in the previous phase are to be selected to fill the job vacancies. This selection is based not only on the competency of candidates, but also on the importance of each position. Regarding the concept of natural selection in genetics, GA can arrive at a set of candidates that satisfies all the PAP conditions, resulting in an optimal or near optimal solution.

To summarize, a new algorithm is developed as a combination of FIS (to evaluate candidates) and GA (to optimize the solution) for PAP solving. The knowledge of HR managers is encapsulated in FISs. So, by gathering data from candidates (by means of questionnaires, forms, interviews, etc.), input data is prepared for this algorithm. Candidates are evaluated through FISs while the GA optimizes the combination of selected candidates according to the restrictions of each defined situation.

This paper is organized as follows: Section 2 provides an introduction to fuzzy logic and FISs. Section 3 introduces the GA while section 4 introduces the proposed algorithm as a means of dealing with the PAP. Section 5 details an application through a case study. Results and analysis are shown in section 6. Finally, Section 7 provides the conclusions of this study.

Fuzzy Logic and Fuzzy Inference System

Every day in our decision-making process, we face situations in which the obtained and available data are imprecise and vague in nature. In dealing with such conditions, using exact and precise modeling is not always an optimal choice (P. Rabiei & Arias-Aranda, 2018). In order to handle uncertainty and ambiguity, Zadeh (1965) introduced fuzzy logic theory to deal with situations in which boundaries are not exactly defined.

The process of decision making in management is usually tied to different degrees of ambiguity and uncertainty. FIS captures experts' knowledge in the form of if-then rules and formulates the way in which humans think when data is uncertain, linguistic, imprecise or insecure (Ruzic, Skenderovic, & Lesic, 2016). In the literature, the use of FISs on decision making for management involves both a wide range of applications to measure HRM performance (Ruzic et al., 2016), and support for the retention strategies of human capital (Kalali, 2015); as well as supplier selection (Amindoust, Ahmed, Saghafinia, & Bahreininejad, 2012; Carrera & Mayorga, 2008; Tahriri, Mousavi, Haghighi, & Dawal, 2014) or risk assessment systems (Bukhari, Tusseyeva, & Kim, 2013) among others.

In this survey, before assigning candidates to job vacancies, their competency for each vacancy should be evaluated. However, a noticeable number of indexes (such as self-confidence, attention to detail or team-working abilities) are of a qualitative nature with different degrees of uncertainty. HR managers are responsible for evaluating candidates. By applying the FIS, the HR managers' knowledge and reasoning system can be encapsulated in a mathematical model. Hence, the created FIS is able to evaluate the competency of a large number of candidates based on raw data in an effective and efficient way through the following key conceptions:

Linguistic variable. A linguistic variable is a variable whose values are expressed in linguistic terms. This concept is very useful in handling situations which are too complicated or not sufficiently well defined to be described in conventional quantitative expressions (Zimmermann, 2011). For instance, “previous experience” is a linguistic variable whose values could be: very low, low, medium, high, very high, etc. These linguistic values are represented by fuzzy numbers.

Membership function. In fuzzy logic the concept of membership function determines how much a variable belongs to a set. Suppose we have a range called A. Membership function μ is a function from A to the real unit interval [0 1]: $\mu: A \rightarrow [0\ 1]$. The membership function is usually denoted by $\mu_A(x)$ and determines the membership degree of x in the fuzzy set $\tilde{A}$. If $\mu_A(x) = 0$, it means that x certainly is not a member of A. If $\mu_A(x) = 1$, it means that x is definitely a member of A. other values between 0 and 1 means that x is partially a member of fuzzy set A and its degree of membership equals to $\mu_A(x)$ (Zadeh, 1965).

Fuzzy if-then rules. Fuzzy if-then rules are expressions in the form of $If\ x\ is\ A, then\ y\ is\ B$. Actually, these kinds of expressions formulate conditional statements. A and B represent fuzzy sets defined by their membership functions. The if-part is called premise part and x is called input variable. The Then-part is considered as a consequent part and y is the output variable. A simple fuzzy if-then rule could be as follows: If price is reasonable, then value is high.

Price and value are linguistic variables. Moreover, reasonable and high are linguistic values as well which are defined in the form of membership functions. Also, “If price is reasonable” is the premise part and “then value is high” is considered as consequent part. Also, the core part of FISs is constructed by fuzzy if-then rules (Jang, 1993).

Fuzzy Inference Systems

FIS performs a kind of mapping from an input space to an output space by means of fuzzy logic (Figure 1). In this study, one type of FISs, known as Mamdani-type (Mamdani & Assilian, 1975), is used. According to (Jang, 1993), FIS consists of five blocks (Figure 1):

(1) Rule base. This block contains all the fuzzy if-then rules;
(2) Database. The main segments of fuzzy rules are fuzzy sets. The membership functions of fuzzy sets are defined in the Database;
(3) Inference unit. It performs inference operations on the rules;
(4) Fuzzification interface. Fuzzification is the process of transforming a crisp input value (A given numeric value within the range of linguistic variables) into its equivalent degree of membership in associated linguistic values;
(5) Defuzzification interface. The Fuzzy result, obtained in the inference process, should be transformed into a crisp output value. This transformation is known as defuzzification.

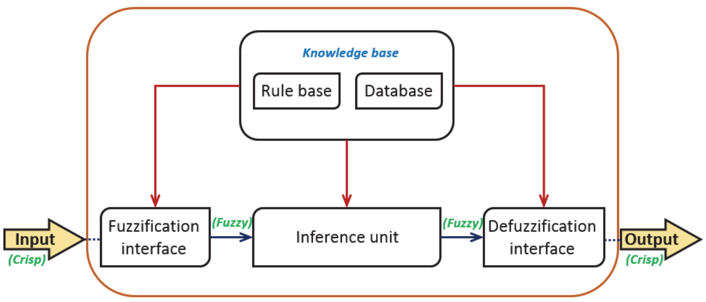


Fig. 1. FIS. Source: Adapted from Jang (1993)

An example of how a Mamdani FIS (in the process of mapping from input space to output space) works is illustrated in Figure 1. Assuming two fuzzy sets in two linguistic variables in input space: “Basic Computer Skills” and “Previous Experience” as well as the linguistic variable “Competency” in output space; the process of fuzzy reasoning could be divided into five steps (Jang, 1993):

(1) Fuzzifying input variables. In this step, the input numerical values are transformed into their equivalent degrees of membership in associated fuzzy sets. In Figure 2, it is determined by intersecting input values to their related fuzzy sets. This process is known as fuzzification;
(2) Apply fuzzy operator. In the premise part of the first rule (If Basic Computer Skills are Low and Previous Experience is Medium, then Competency is Medium), there are two sets: “Basic Computer Skills are Low” and “Previous Experience is Medium”. Some kinds of fuzzy operators known as T-norm operators (such as multiplication or minimum operator) are required in order to combine the membership values of mentioned sets obtained in the fuzzification process. As depicted in Figure 2, a minimum operator is applied and the rule weight w1 (also known as firing strength) is obtained. The same process should be carried out for the second rule (If Basic Computer Skills is Medium and Previous Experience is High, then Competency is High) to calculate w2;
(3) Apply implication method. The consequent part of each if-then rule is also a fuzzy linguistic set. Based on the weight (firing strength) of each rule obtained in the previous step, the fuzzy set of the consequent part is truncated. This process is known as implication;
(4) Apply aggregation method. The truncated fuzzy sets in the consequent part of all the rules determined by implication method are combined to form a single fuzzy set. In order to achieve this goal, an aggregation method is implemented. There are various aggregation operations such as max or sum functions. Function max is applied in this example since it is easy to implement and well accepted;
(5) Defuzzification. This step is exactly the opposite of fuzzification. The combined fuzzy set from the aggregation process is defuzzified in order to produce a single scalar value. As it is shown in Figure 2, the centroid method which returns the center of area under the curve is used in the defuzzification step in this example.

As it is shown, fuzzy reasoning determines how the output parameter “Competency” of an employee is calculated based on the input parameters of “Basic Computer Skills” and “Previous Experience”. Note that steps 2, 3 and 4 are carried out in the inference unit.

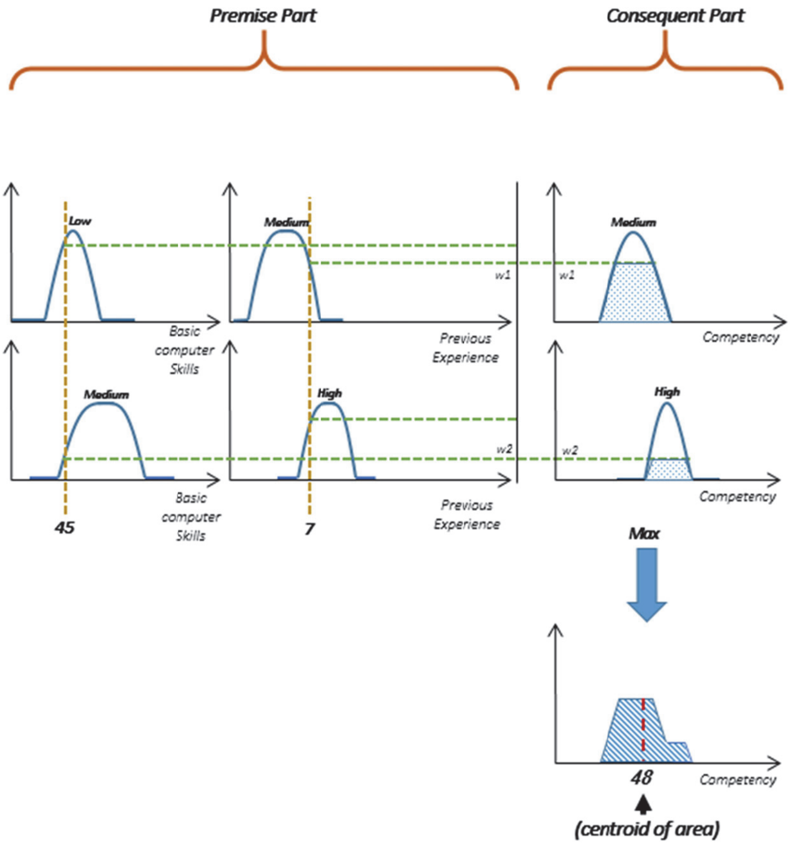


Fig. 2. Fuzzy if-then rules and fuzzy reasoning mechanisms. Source: Adapted from Jang (1993)

Genetic Algorithm

The concept of GA was first introduced by Holland (1975). GA is a well-known optimization search methodology inspired by natural selection and evolution in biological systems to generate optimal or near optimal solutions (Herrera et al., 2001). This algorithm is an alternative to traditional heuristic methods (Gupta, Mehlawat, & Mittal, 2013).

Regarding the defined problem, each chromosome (a vector of data) is actually a feasible solution. GAs produce a set of feasible chromosomes as potential solutions for the problem. The utility of chromosomes is evaluated through a function called fitness function. Over iterations, by applying genetic operators, GAs evolve the chromosomes in order to find the optimal solution (Mitchell, 1998). Iterations continue until a stopping condition (e.g., the number of generations or no improvement in the population for some specific iterations) is met. The basic structure of a GA is depicted in Figure 3. There are six key concepts in GAs:

1. Chromosome. The structure of a possible solution for the problem is presented as a vector. This simple vector is called a chromosome (Toroslu & Arslanoglu, 2007). Each chromosome conceptually can be partitioned into genes. The specific position of each gene in the chromosome is called locus and its value is known as allele (Mitchell, 1998). The structure of a chromosome is depicted in Figure 4;

2. Population. In each generation, the set of chromosomes (possible solutions) is known as a population (Gupta et al., 2013);
3. Fitness function. It is an evaluation function which measures the fitness of each chromosome according to the desired optimal solution (Toroslu & Arslanoglu, 2007);
4. Selection. The way in which chromosomes are selected from the population for mating, mutation or generating new population is determined by the selection operator. The more fit chromosomes, the higher chance of reproducing and passing their genes to the next generation (Mitchell, 1998);
5. Crossover. It is a main genetic operator. This operator takes two parent chromosomes and by recombining them, produces two child chromosomes (offspring) (García-Pedrajas, Ortiz-Boyer, & Hervás-Martínez, 2006);
6. Mutation. It is also a main genetic operator which randomly alters the value of some genes in the chromosome (Mitchell, 1998).

Applying GA has some significant advantages:

- GAs are flexible algorithms which can be merged with heuristic methods and make hybrid algorithms (Gupta et al., 2013; Niknafs, Denzinger, & Ruhe, 2013).
- GAs are adaptive. They can draw out information in an initially unfamiliar search space to develop further searches in more appropriate subspaces. This makes GA more powerful compared to classical search tools such as heuristic methods especially in large, discontinuous, complex and poorly understood search spaces (Herrera et al., 2001).
- GAs can avoid local optimums (A. Rabiei, Sayyad, Riazi, & Hashemi, 2015) and converge to the global optimum (Gupta et al., 2013) quickly and reliably. However, there is no guarantee that the global optimum will be reached (Herrera et al., 2001).
- It is not necessary to have an extensive mathematical understanding of optimization problems (Niknafs et al., 2013).

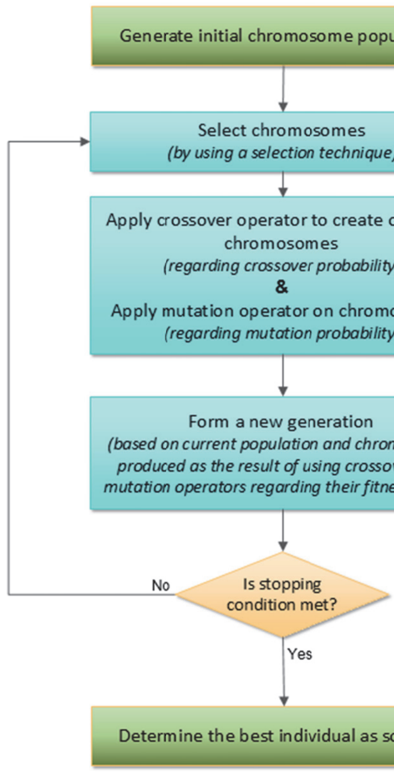


Fig. 3. The basic structure of a GA

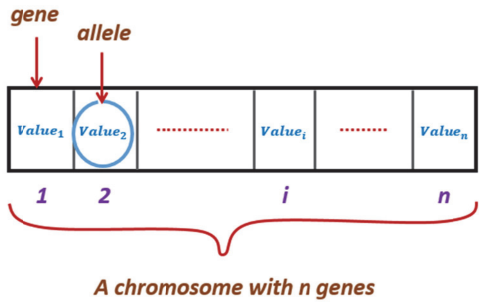


Fig. 4. Structure of a chromosome

According to the literature, GAs are suitable methods in search and optimization problems (Gupta et al., 2013). These algorithms are very successful in multi-objective NP-hard optimization problems (Gupta et al., 2013; Toroslu & Arslanoglu, 2007). In the field of management, GAs have a wide range of applications in Solving PAP (Niknafs et al., 2013) and Worker assignment (Mutlu, Polat, & Supciller, 2013), personnel staffing (Jiménez-Domingo, Colomo-Palacios, & Gómez-Berbís, 2014), assignment problems (Tailor & Dhodiya, 2016; Tosun, Dokeroglu, & Cosar, 2013; Yang, Peng, Jiang, Wang, & Li, 2014), job-shop scheduling problems (Driss, Mouss, & Laggoun, 2015), job scheduling models (Liu, Luo, Zhang, Zhang, & Li, 2013), manufacturing scheduling problems (Gladkov, Gladkova, & Leiba, 2014), production-distribution planning problems (Jia, Wang, & Fan, 2014), resource assignment (Gupta et al., 2013); credit risk assessment (Oreski & Oreski, 2014) and energy management (Arabali, Ghofrani, Etezadi-Amoli, Fadali, & Baghzouz, 2013; Soares, Antunes, Oliveira, & Gomes, 2014), among others.

FIS and GA to solve PAP

PAP involves the assignment of candidates to job positions based on their competencies. In the literature, competency is defined as the ability to perform the defined tasks in an effective way (Różewski & Małachowski, 2009). This ability is, in fact, a mixture of knowledge, skills (improved through experience), behaviors and attitudes (Suleman & Suleman, 2012). Assessing individual competencies in a precise way becomes a challenge because of the nature of human attributes. As a result, firms face situations in which decision making is influenced by uncertainty and vagueness. Fuzzy logic is a suitable approach to deal with these situations. Regarding competencies assessments, fuzzy logic is widely used. Some examples are unit competence evaluation (Pépiot, Cheikhrouhou, Fürbringer, & Glardon, 2008); firm competence (Amiri, Zandieh, Soltani, & Vahdani, 2009) or employee competence (Golec & Kahya, 2007; Guillaume et al., 2014; Suleman & Suleman, 2012).

Our approach in this study benefits from the ability of FIS in modeling human qualitative knowledge and reasoning combined with GA (to optimize the solution) in dealing with the PAP. This approach considers that there are n job vacancies (positions) denoted by P_i $i = 1,2, \dots, n$ and m candidates, denoted by C_j $j = 1,2, \dots, m$. m candidates are to be assigned to n positions where $m > n$. In dealing with PAP, the evaluating process involves two phases:

1. Evaluating individuals. The problem to be solved involves the assignment of candidate C_j to position P_i. So, the competency of candidate C_j for occupying the position P_i needs to be evaluated. In order

to reach this goal, experts (HR managers), first determine the required knowledge, skills, behaviors and attitudes of the right candidate. In the next step, experts determine the level of aptitude of candidate C_j for the job P_i by obtaining information from him/her through a range of different sources such as forms, interviews, questionnaires and resumes among others. In this way, it can be determined to what extent candidate C_j is suitable for occupying position P_i.

For each position, in this approach, the experts' knowledge is encapsulated in a FIS. By applying designed FISs on candidates' information, their competency for each available position can be measured.

2. Evaluating a solution. With n positions, n candidates need to be selected. A potential solution is:

$$Solution = \left(C_{P_1}, C_{P_2}, C_{P_3}, \dots, C_{P_n}\right). \tag{1}$$

It means candidate C_{P_1} is assigned to the first position, while C_{P_2} is assigned to the second available position, etc. FIS is applied to evaluate the competency of each candidate. The fitness value of the solution is not simply the summation of each individual competency, since all the positions are not of the same importance. Indeed, when candidates have the competency for occupying more than one position, managers would select the most competent candidates for the most vital positions. In this case, GAs help to optimize the solution. Therefore, weights are necessary to determine the importance of each position. The weight of position P_i is denoted by $W_i \;\; i = 1, 2, \dots, n$ to determine the importance of position P_i. Hence, the fitness value of the solution would be:

$$Fitness\ value = \sum_{i=1}^{n} W_i \times Competency(C_{P_i}) \tag{2}$$

In previous studies, in addition to classic methods, different innovative methods such as a priority scale based on AHP (De Feo & De Gisi, 2010), an integrated criteria weighting framework (Iwaro, Mwasha, Williams, & Zico, 2014) or a fuzzy AHP-TOPSIS method (Kusumawardani & Agintiara, 2015), among others, are used in defining weights. Determining the importance of positions is a qualitative situation with different degrees of ambiguity. So, in this study, to specify the importance of each position, we benefit from a set of linguistic labels in order to prioritize job vacancies.

In summary, FIS emerges as a useful tool to evaluate candidates' competency regarding different positions. Besides, GA enables us to reach the optimum or excellent near optimum solution in which the most competent individuals are assigned to the most important positions. In order to apply this, an algorithm is proposed involving ten steps as follows:

Step 1: Identification of job vacancies (positions) and their importance in the organization

In the first step, HR managers determine which positions are to be filled. Positions are denoted by $P_i \;\; i = 1,2, \dots, n$. where n is the number of positions. A set of linguistic labels indicate the importance of each position in normal linguistic terms according to HR managers. The weights of positions are denoted by $W_i \;\; i = 1,2, \dots, n$. All positions should be occupied and each chosen candidate should be assigned to only one position.

Step 2: Identification of critical factors for occupying each position

In order to hire a new employee for a job vacancy, some critical factors need to be taken into account in the process of assessing a candidate. This step involves preparing a list of such critical factors for all the positions separately.

Step 3: Collecting data from candidates

Data from candidates is collected by proper means such as interviews, resumes, etc. based on the critical factors for occupying each position obtained in the previous step.

Step 4: Implementation of a FIS for each position to evaluate the competency of candidates

For each position, a FIS should be implemented in order to evaluate candidates' competency. For each FIS, determine all its five main blocks which discussed earlier in section 2.1.

So far, a set of FISs is implemented to evaluate the candidates' competencies for occupying positions regarding the various instances of the critical factors required. In the next steps, a GA to optimize the solution of PAP is implemented.

Step 5: Designing the structure of chromosomes

In designing a GA, the first step involves encoding a possible solution of the defined problem as a simple vector (or chromosome). There are n positions to be assigned to m candidates where the number of positions is smaller than the number of candidates($n < m$).

Step 6: Implementation of the fitness function

In order to evaluate the generated solutions, it is necessary to establish the closeness of the specific solutions (chromosomes) to the optimal solution. The fitness function measures the fitness of a solution (chromosome). In step 1, the importance of each job vacancy is determined. Also in step 4, considering each position, a FIS is implemented to evaluate the candidates' competency for each position. Actually, FIS is the core of the fitness function in the GA. As positions are of different importance, the fitness value of a solution is not simply the summation of each individual competency. Assuming that there are n positions denoted by $P_i \;\; i = 1, 2, \dots, n$, the weight of position P_i is denoted by $W_i \;\; i = 1,2, \dots, n$. The fitness value of a solution is:

$$Fitness\ value = \sum_{i=1}^{n} W_i \times Competency(C_{P_i})$$

In this way, the competencies of candidates who could occupy several positions are awarded higher fitness values, which results in their placement in the positions of higher priority.

Step 7: Definition of selection techniques

The concept of selection includes how chromosomes are selected for genetic operators (crossover and mutation), as well as which chromosomes are passed to the next generation. The most suitable chromosomes (for genetic operators and also generating new population) must be selected to achieve more compatible solutions (Mitchell, 1998). Diversity in chromosomes is of great importance and should be taken into account in the selection process. So, this step includes defining proper selection techniques for generating new populations and also choosing chromosomes for genetic operators (crossover and mutation).

Step 8: Implementation of a crossover operator

The crossover operator generates two child chromosomes (offspring) by taking two parent chromosomes and recombining them. It is crucial to implement an adequate crossover operator, taking into account the characteristics of the defined problem.

Step 9: Implementation of a mutation operator

The mutation operator randomly alters the value of some genes in the chromosome to keep diversity in the population. Regarding the characteristics of the defined problem, a proper mutation operator is implemented.

Step 10: Tuning up GA parameters and running the algorithm

The parameters of the algorithm are set and run. The parameters are the number of generations, number of individuals, crossover probability, mutation probability and tournament size. Figure 5 shows the steps of the proposed algorithm.

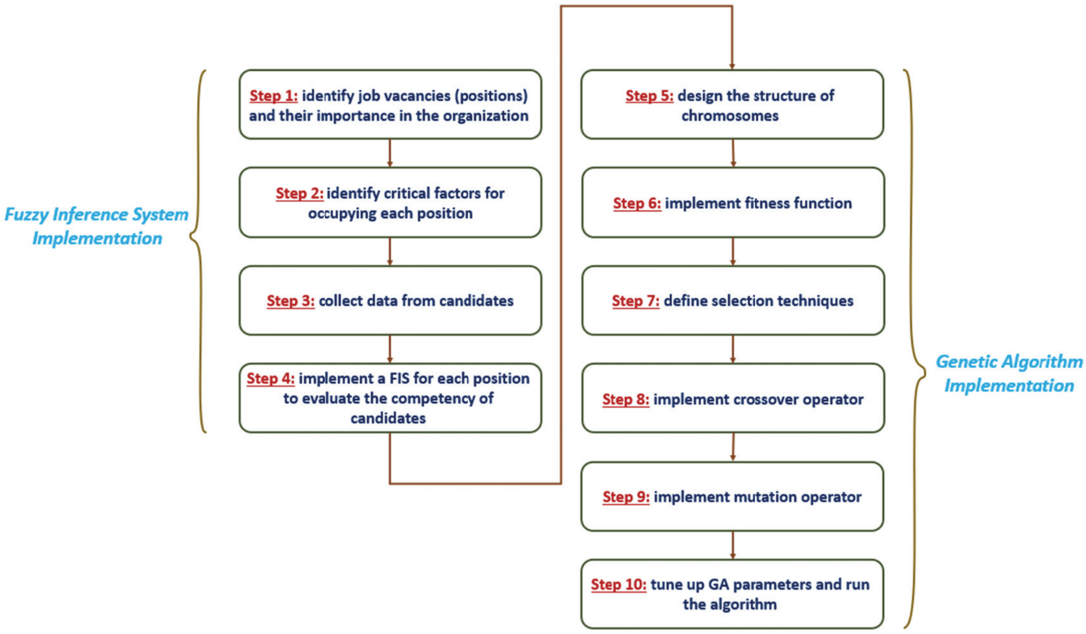


Fig. 5. The framework of the proposed Algorithm

Case study

The described algorithm has been applied in a real PAP for the Aidin company. This company in Iran manufactures and exports a wide range of chocolate products. Through interviews with HR managers, job vacancy details and priorities, as well as critical selection factors for candidates were obtained. This case demonstrates both the application of the algorithm and the subsequent evaluation by HR managers. The steps taken were as follows:

Step1: Identify job vacancies (positions) and their importance in the organization

Three positions were to be filled. Also, to specify the importance of each position, a set of nine linguistic labels introduced by Herrera et al. (2001) were used. Linguistic terms were in Triangular Fuzzy Numbers (TFNs) and defined in the [0, 1] interval as follows:

$$Weight = \{Essential, Very\ High, Fairly\ High, High, Moderate,$$
$$Low, Fairly\ Low, Very\ Low, Unnecessary\}$$

Weight linguistic term set is depicted in Figure 6 with its parameters given in Table 1. The weight of position P_i is a linguistic variable denoted by W_i $i = 1,2, \dots, n$. Positions, job descriptions and their importance are shown in Table 2.

Step 2: Identify critical factors for occupying each position

HR managers assess and hire new employees. As a results of interviewing these managers, critical factors were determined for each position as listed in Table 3.

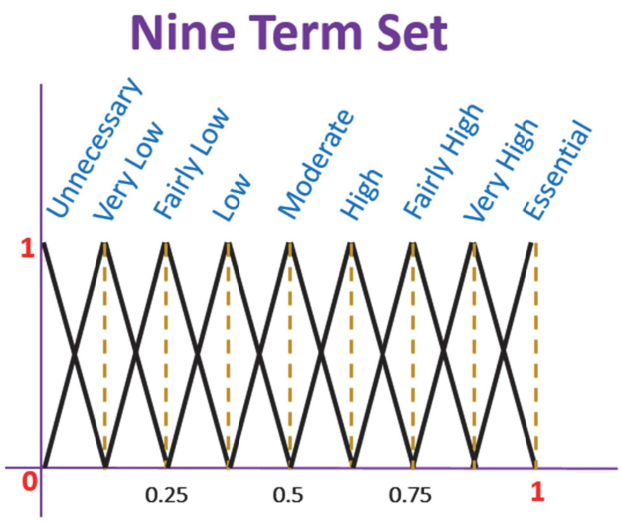


Fig. 6. Linguistic labels

Table 1. Weight linguistic term set

Linguistic Variable	Parameters
Essential	(0.875, 1, 1)
Very High	(0.75, 0.875, 0.1)
Fairly High	(0.625, 0.75, 0.875)
High	(0.5, 0.625, 0.75)
Moderate	(0.375, 0.5, 0.625)
Low	(0.25, 0.375, 0.5)
Fairly Low	(0.125, 0.25, 0.375)
Very Low	(0, 0.125, 0.25)
Unnecessary	(0, 0, 0.125)

Table 2. Positions to be filled and their weights

Position (P_i)	Position name	Job description	Position weight (W_i)
P_1	Accountant	It involves preparing special financial reports and summarizing current financial status precisely; Also, preparing asset and capital account entries by compiling and analyzing account information. Being familiar and having experience in preparing balance sheet, profit and loss statement, and other reports are valued.	Very High
P_2	Salesman	This position involves presenting, promoting and selling products to existing and potential customers; communicating and negotiating regularly and easily with customers. Knowing the market and having experience as a sales representative is of necessities.	High
P_3	R & D employee	It includes handling R&D project teams; understanding the company's technology and processes (through technical background and relevant experience in chocolate industry); as well as conducting online researches and computer analysis.	Essential

Table 3. Critical factors to obtain each position

Position (P_i)	Position name	Critical factors to get the position
P_1	Accountant	Attention to detail Basic Computer Skills Previous related experience
P_2	Salesman	Self confidence Extraversion Previous related experience
P_3	R & D employee	Team working abilities Previous related experience Basic computer skills

Step 3: Collect data from candidates

Three different methods to get candidates' information were applied: Interview, questionnaire and resume. Attention to detail and team working abilities were assessed on a scale of 0-100 during the interview. Basic computer skills and previous related experience were obtained through the candidates' resumes. Finally, a questionnaire was used in order to assess candidates' self-confidence and extraversion. Details are shown in Table 4.

Table 4. Methods of collecting data regarding critical factors

Critical Factor	Method of collecting data	Scale
Attention to detail	Interview	0-100
Team working abilities		0-100
Basic Computer Skills [a]	Resume	0-100
Previous related experience		0-30 [b]
Self-confidence	Questionnaire	1-5[c]
Extraversion		1-5[c]

[a] Based on International Computer Driving License (ICDL) score.
[b] Scale: years.
[c] Scale: 1=totally disagree, 2=disagree, 3=no opinion, 4=agree, 5=totally agree.

The self-confidence questionnaire developed by Day and Hamblin (1964) and updated by Veale and Quester (2007) was adopted. Also, extraversion items were implemented from Benet-Martinez and John (1998). Demographics of candidates are collected in Table 5. Scale reliability is measured by means of Cronbach's alpha. This coefficient is 0.81, 0.84 for Self-Confidence and Extraversion questionnaires respectively.

Table 5. Demographics of candidates

Demographic factor	Range	Number of candidates
Age (Year)	<25	2
	26-30	11
	31-35	2
	36-40	4
	>40	16
Experience (Year)	<5	8
	6-10	11
	11-15	3
	16-20	6
	>20	7
Gender	Female	11
	Male	24
Level of educa-tion	Diploma	3
	Associate Degree	13
	Bachelor Degree	16
	Master Degree	3

Step 4: Implement a FIS for each position to evaluate the competency of candidates

For each position (Accountant, Salesman and R&D employee), a FIS was implemented by designing its five blocks:

1. Fuzzification interface. Fuzzifying was performed through intersecting input values to their related fuzzy sets;
2. Defuzzification interface. The centroid method was applied for defuzzification;
3. Inference unit. In the fuzzy inference process, the standard max-min algorithm was used. For each rule, in order to evaluate the membership grade of premise part, the minimum operator was applied. Also, the maximum operator was used for aggregation;
4. Database. Fuzzy linguistic variables and their parameters for all six critical factors obtained in step 2 and competency were designed based on four HR managers' points of view. In this case, Triangular and trapezoidal membership functions were applied;
5. Rule base. For each position, the knowledge of four experts (HR managers) on assessing candidates' competency are encapsulated in the form of fuzzy if-then rules.
6. Note that fuzzification, defuzzification and inference strategy are the same in all three designed FISs.

Step 5: Design the structure of chromosomes

This step involves encoding a possible solution as a chromosome. In this study, we have three positions and 35 candidates. A possible solution is shown in Figure 7. As it is depicted, our chromosome has three genes (same size as the number of positions). The value of first gene is C_8. It means that candidate number 8 is assigned to the first position (Accountant). Similarly, candidate number 4 will occupy the second position (Salesman) and candidate number 7 goes to the third position (R&D employee).

Note that all positions are occupied by candidates and each candidate in the chromosome is matched to only one position.

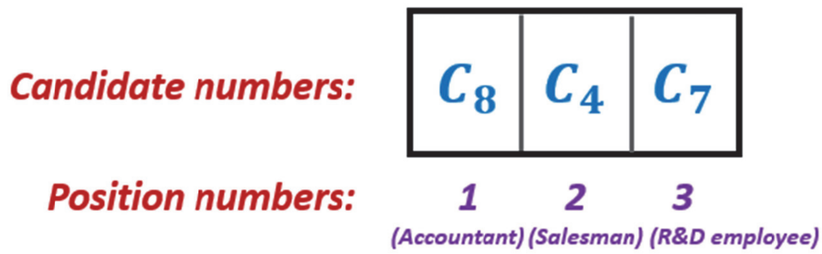


Fig. 7. Structure of a chromosome

Step 6: Implement fitness function

The fitness value of each solution (chromosome) is the weighted sum of candidates' competencies in the positions they are to be hired. In step 1, position weights are determined (Table 1). Also, competency of each candidate (in the position he/she is assigned) is assessed using FISs implemented in step 4. Now, candidates' competency is multiplied by their position weight. Summation of obtained values, forms the fitness value of the solution. These operations are taken place in fitness function. There are three job vacancies, so:

$$Fitness\ value = \sum_{i=1}^{3} W_i \times Competency(C_{P_i}) \quad (3)$$

Step 7: Define selection techniques

Three selection techniques to generate new population were defined and the chromosomes for genetic operators (crossover and mutation) were selected:

In order to form a new generation, the elitism introduced by De Jong (1975) is amongst the most popular selection techniques in the literature. In this method, some best solutions in each generation are preserved and passed directly to the next generation. Additionally, the best solutions are retained over generations until some fitter chromosomes are found. Using elitism has improved GA performance in the literature (Ahmed & Deb, 2013; Bhateja & Kumar, 2014; Rao & Patel, 2013; Wong, Sharma, & Rangaiah, 2016). In this case, we preserved 10% of the fittest chromosomes of the current population to the next generation directly without performing crossover and mutation operations.

Similarly, in selecting chromosomes for mating or mutation, the same logic was followed. The individuals with higher fitness are more likely to be elected as parents in order to pass their high-quality genes to the next generation. In any case, as a matter of probability, even worse individuals have the chance to be chosen but in lower probabilities. In this way, the algorithm is prevented from being trapped in the local optimum since the diversity is maintained in the population. In the literature, a variety of selection methods are introduced: Roulette wheel selection, stochastic universal sampling, steady-state selection, tournament selection and Boltzman selection, among others (Mitchell, 1998). Two selection strategies were used in this study: Tournament selection and proportional roulette wheel selection (Razali & Geraghty, 2011):

Tournament selection. This is an efficient and easy-to-implement selection strategy. n individuals are randomly selected from the population and compete with each other. The most convenient one wins the competition and will be selected. The number of selected chromosomes to participate in the tournament is known as tournament size (Ts). Figure 8 depicts how tournament selection strategy acts if tournament size is set to the population size, the fittest chromosome will be selected. Also, smaller values of tournament size lead to more diversity in selecting chromosomes. In this case, we set tournament size to three.

Proportional roulette wheel selection. In this selection strategy, the probability of a chromosome to be selected to pass on its genes to the next generation is exactly related to its fitness. Assuming a circular wheel divided into n (the number of chromosomes in the population) segments, each pie represents a chromosome and its share is proportional to the individual fitness. The more convenient the chromosome, the large the corresponding pie on the wheel. When the wheel is spun, the pie indicated by the pointer when it stops will be selected. In this method, a selection pressure is on the most convenient chromosomes. However, all individuals have the chance to be chosen. As a result, the diversity is retained in the population. The mechanism of Proportional roulette wheel selection is illustrated in Figure 9.

Considering selection strategies in the literature, tournament selection and proportional roulette wheel selection have received plenty of attention because of their acceptable performance (Butz, Sastry, & Goldberg, 2003; Cui & He, 2016; Malhotra, Singh, & Singh, 2011; Sharma, Singh, & Sharma, 2012; Zhong, Hu, Zhang, & Gu, 2005). In this case, we applied both described selection techniques in order to compare their performance.

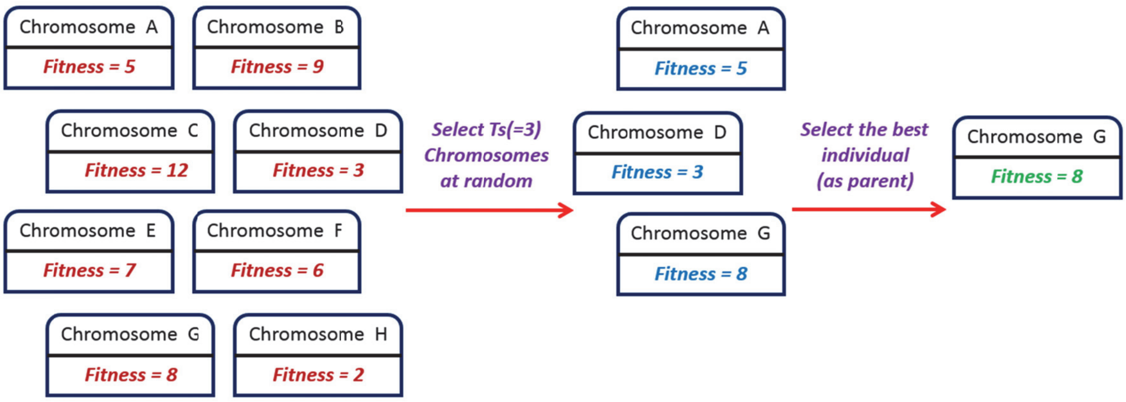


Fig. 8. Tournament Selection

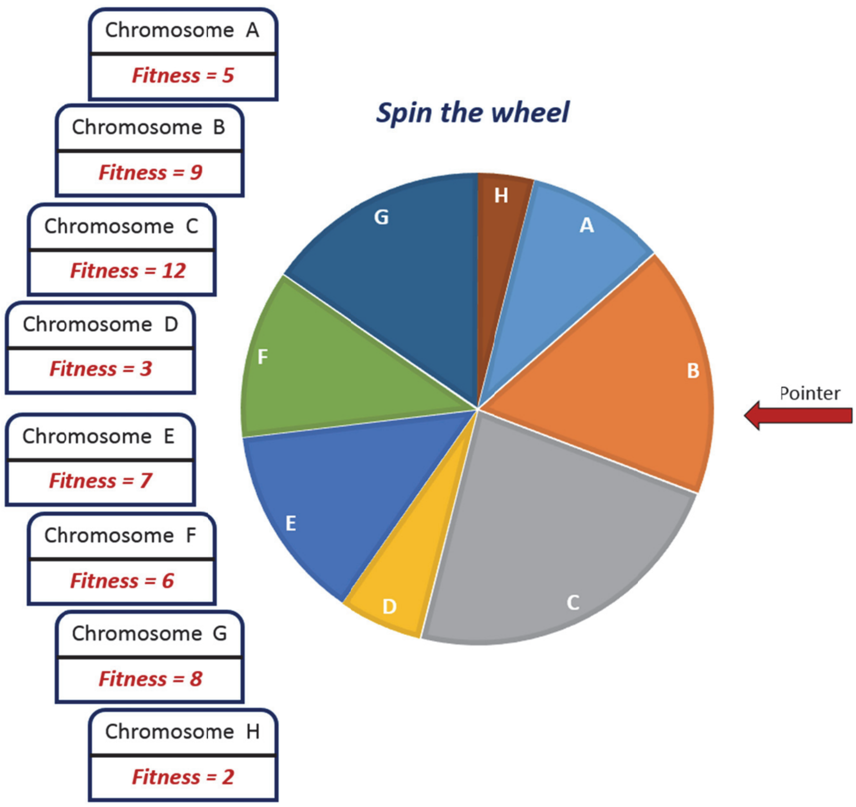


Fig. 9. Proportional roulette wheel selection

Step 8: Implement crossover operator

By using a crossover operator, we combine two parent chromosomes together and reproduce two child chromosomes known as offspring. Ordinary crossover operators such as single-point crossover, multiple-point crossover and uniform crossover are used extensively in the literature. However, in this case, we have a permutation chromosome which means each candidate can only occupy one position. Applying the mentioned crossover operators may lead to producing invalid chromosomes. So, a more advanced crossover is used to generate feasible permutation chromosomes (Herrera et al., 2001).

Figure 10 shows how offspring are produced by combining parent chromosomes. Consider that we have a chromosome with five genes. In the first step, in each offspring we keep repeated candidates and the ones which are in the same position in the other chromosome, unchanged. Then, amongst the remaining genes, we randomly select some of them and exchange their values. In this way two valid offspring are obtained.

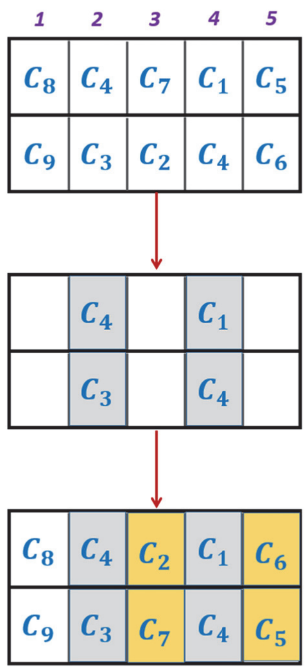


Fig. 10. Permutation crossover

Step 9: Implement mutation operator

The purpose of mutation operator is to retain diversity in the population. In cases in which each gene in the chromosome is a bit, the simplest way is to select one or more random bits and alter their content. However, this method is not applicable in this case. So, we use two different mutation operators suitable for permutation based chromosomes:

1. Swap mutation. In this mutation type, first we choose two genes (positions) in the chromosome randomly. Then we interchange their values.
2. Inversion Mutation. This mutation type involves selecting a subset of genes in the chromosome and inverting the entire values in the subset.

Each time we have to call a mutation operator on a chromosome, one of the mentioned mutation operators is applied randomly. In this way, a new reliable permutation chromosome is produced. Figure 11 demonstrates how these mutation operators work for a chromosome with five genes.

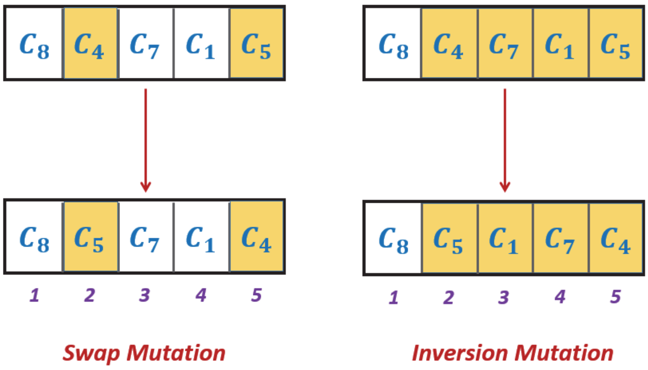


Fig. 11. Mutation Operators

Step 10: Tune up GA parameters and run the algorithm

GA parameters used in this case are listed in Table 6. After setting the parameters, we run the algorithm using MATLAB R2013b to get the optimized solution for the PAP. The obtained solution is available in Table 7.

Table 6. GA parameters

GA Parameters	Values	Description
Number of generations	100	*Number of algorithm iterations. It is in fact algorithm termination criteria*
Number of individuals (known as pop size)	30	*Number of chromosomes in each generation*
Crossover probability	80%	*What percentage of the population will be picked for mating*
Mutation probability	10%	*What percentage of the population will be picked for mutation*
Tournament size	3	*The number of selected chromosomes to participate in the tournament (in tournament selection)*

Table 7. Solution obtained by the GA

Position (P_i)	Position name	Position weight (W_i)	Selected Candidate (C_i)
P_1	Accountant	Very High	C_{13}
P_2	Salesman	High	C_{32}
P_3	R & D employee	Essential	C_1

Results and analysis

In this section, the overall value and efficiency of the proposed algorithm was evaluated and the performance of GA regarding two different selection techniques was assessed.

System evaluation

To evaluate the algorithm, the main indexes are its efficiency and speed, the accuracy of experts' encapsulated knowledge and the ability of making optimal decisions. Experts evaluated the algorithm. Ten HR managers of the firm were asked to assess the mentioned indexes on a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. Results are available in Table 8.

Results demonstrate that HR managers rated the proposed algorithm and system designed in Matlab highly with the mean score of 3.9. So, according to the positive evaluation of experts, the proposed algorithm and system is promising in dealing with PAP. The experts' knowledge is embedded well in the FIS and GA optimizes the solution effectively considering the importance of positions.

GA performance with different selection techniques

GA performance comparison is based on the Number of Function Evaluation (NFE) and the number of generation in which the solution with maximum profit is obtained. Note that NFE indicates how many times the fitness function is called or how many potential solutions are evaluated.

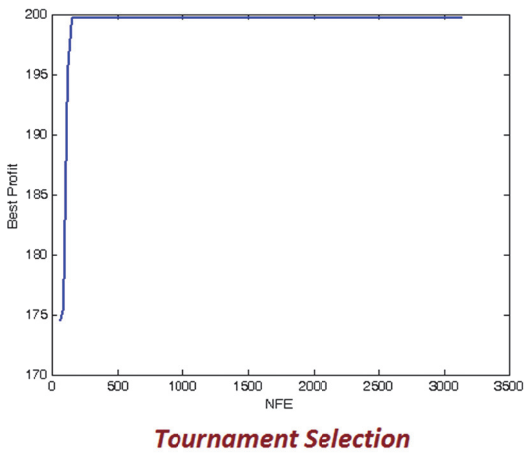
Regarding each selection technique (tournament selection and proportional roulette wheel selection), we run the algorithm ten times. For each one, the solution with the highest fitness value and the lowest NFE was taken as the final result. Summarized results are given in Table 9. Also, Figure 12 depicts performance graphs. Both selection techniques reached the same fitness value of 199.6764. The tournament selection found the solution in the 4^{th} iteration by evaluating 154 solutions (NFE) while, proportional roulette wheel selection did the same thing in the 6^{th} generation by evaluating 216 solutions. Figure 12 shows that tournament selection reaches the solution sooner. Therefore, tournament selection outperforms the proportional roulette wheel selection in gaining acceptable and high quality solution with lower cost.

Table 8. Proposed algorithm evaluation questions and results

Questions	Mean	Standard Deviation
1. System is able to consider critical factors in selecting candidates properly	4.1	0.876
2. System takes into account position importance properly (makes optimal decisions)	4	0.667
3. System really helps in selecting suitable candidates.	3.9	0.994
4. System response time is acceptable.	4.4	0.516
5. I would recommend my colleagues to use this system	3.4	0.966
6. I would like to use this system in hiring new personnel	3.6	0.699
	Total mean: 3.9	

Table 9. Performance results of GA selection techniques

	Tournament Selection	Proportional Roulette Wheel Selection
Fitness Value	199.6764	199.6764
NFE	154	216
Generation Number (in which solution is obtained)	4	6



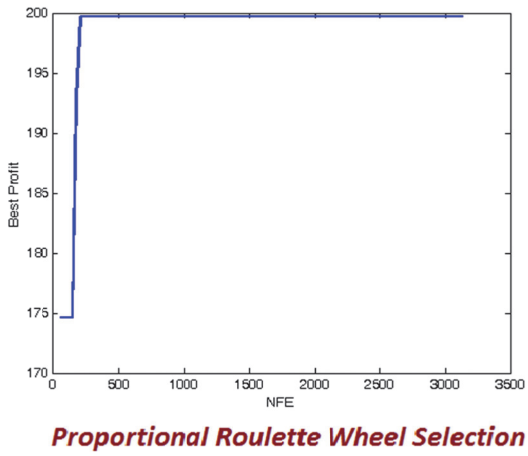


Fig. 12. Performance graphs of GA selection techniques

Conclusion

In this study, a twofold objective was achieved. Firstly, we developed a solution for PAP in an uncertain environment by using a combination of FIS and GA. An algorithm inclusive of two phases was introduced: In the first phase, HR managers' qualitative knowledge and reasoning process was formulated in FISs. So, with raw data alone, these systems were able to evaluate candidates' competency regarding each job vacancy. In the second phase, GA assigned candidates to job vacancies so as to maximize profit by considering the competency of candidates in conjunction with the relative importance of the positions to be filled. Results in the case study were assessed by HR managers. Consequently, the effectiveness of the proposed algorithm pioneering the combination of FIS and GA in dealing with PAP was confirmed.

Secondly, we evaluated GA performance by employing two different parent selection strategies: Tournament selection and proportional roulette wheel selection. Based on the NFE and the number of generation in which the solution with the maximum profit was obtained, both selection techniques were compared. The results revealed that tournament selection outperformed the proportional roulette wheel selection.

In addtiton and due to the nature and circumstances of natural disasters, the existence of heterogeneous needs and organizations involved, personnel assignment effectiveness need to be performed in a timely manner for which this solution can be applied. The proposed algorithm could be adopted to other similar problems in the market as well as emergency situations such as assigning resources to tasks, survival kits to vulnerable zones, products to markets or capitals to investments among others. Also, this study is run in a firm belonging to a specific sector. It could be analyzed, as well, in other industries and situations.

For further studies, we suggest the assessment of other selection strategies (e.g. rank-based roulette wheel selection, stochastic universal sampling, Boltzman selection and steady-state selection) and the comparison of their results with the tournament selection and the proportional roulette wheel selection.

Acknowledgments

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