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Personnel Selection in a Competitive Environment

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Abstract. The personnel selection problem is a classical decision making problem. It refers to the process of choosing candidates who match, possibly to some degree, the qualifications required to perform a certain job. Personnel selection is an important activity for organizations and usually the outcome of a personnel selection method is an overall ranking of the candidates. This paper introduces two new results. First, we propose an alternative approach to the personnel selection problem in which the interaction of two competing decision makers (employers), who must select two subsets of persons from a common list of candidates, is considered. Second, given the rankings of the candidates for each employer, a method based on the game theory is presented to solve this problem.

Keywords. Personnel selection, decision making, game theory.

1 Introduction

Selection of qualified human resources is a key success factor for an organization, especially due to the increasing competitive markets and globalization. Personnel selection is the process of choosing individuals (candidates) who match the qualifications required to perform a defined job in the best possible way and it is aimed at choosing the best candidate to fill a specific vacancy in a company or organization; the personnel selection process has a direct impact on the quality of staff and thus it plays an important role in human resources' management, and the future success of the company strongly depends on the contribution of their personnel in order to keep a competitive place in the market.

Personnel selection is a highly complex problem [1]. Accurate personnel selection allows managers to optimize production costs and to achieve corporative goals; the complexity and importance of the problem calls for analytical methods rather than intuitive decisions. A great deal of attention in the literature has been given to the selection of the most eligible and suitable candidate among alternatives. The personnel selection problem is among the most complex decision problems that are encountered in real life. The contemporary employee selection is a complex decision making process that is expected to be capable of placing the right employees in the right jobs at the right time. Because of its importance, many tools and techniques have been proposed to cope with this specific decision making problem.

Employee or personnel performances such as knowledge, capability, skill, and other abilities play an important role in the success of an organization. The multi-criteria nature and the presence of both qualitative and quantitative factors make it considerably more complex. The multi-criteria nature of the problem makes Multi-Criteria Decision Making (MCDM) methods ideal for solving this problem [2]. MCDM methods deal with the problem of selecting the best alternative from a set of candidates according to a set of objectives rather than just one objective.

Indeed, the complexity of the personnel selection problem requires the application of MCDM methods for a better personnel selection. Consequently, MCDM methods were applied in many studies, among them there are [3, 4, 5, 6, 7, 8] and many others in which the MCMD methods were used to assess candidates depending on the degree to which they meet the requirements and evaluation criteria; these methods provide a model of aggregation of this information. Many well-known methods have been applied to aid decision making and have resulted in tools such as TOPSIS, ELECTRE, PROMETHEE, AHP, incorporating ideas from fuzzy theory, grey theory, computing with words, OWA operators, etc.

The aim in MCDM is to determine an overall preference among alternative options. According to the objective, MCDM methods can be used for ranking alternatives or to make a final decision of choice [6]; for the personnel selection problem the first viewpoint is the most relevant one. In the first case the purpose is to rank the alternatives from best to worst. Obtaining a ranking of candidates is especially interesting when the human resource management is oriented to organize, manage, and lead a work team instead of selecting a single candidate; it contributes to the success of the project and creates a competitive advantage for the organization [9, 10]. Developing the work team improves the people's skills, technical competencies, and, as a whole, the team environment and project performance, which is a critical factor for the success of the project [11].

A common problem in the ranking work is the rank aggregation. Rank aggregation is the problem of combining multiple rankings in a single ranking; that is, given a set of N permutations of n elements, to identify the permutation which represents this set in the best way. A common approach to this problem is to find a permutation that minimizes the sum of the distances to each ranking, where in principle any distance(-like) function on permutations can be used [12, 13, 14].

Most existing studies in personnel selection ignore conflicting preferences and strategic interactions among decision makers due to their competing interests. In this paper the problem is approached from a new perspective: the personnel selection problem is considered in a context of competition. That is, two or more decision makers (employers) want to compose their work teams from a set of N candidates. In order to build the teams, employers rank the N candidates according to their interest; maybe, the decision making methods mentioned before could be used to actually calculate these rankings. After that, they make a selection from the common list of candidates to build their teams (in this paper we consider 2 employers who each need to build a team of N/2 members). In this study, the main focus is on this last step, that is, the composition of the work teams using the ranking for each employer.

In general, the appropriate approach to deal with this type of conflict resolution problem is the Game Theory (GT) [15]. It is often seen as an essential tool, especially when there are conflicting objectives. The effective and efficient strategic decision making is the backbone for the success of a business organization, and these decision making processes should take into account its competitors. Therefore, a suitable framework to model this strategic decision making processes by business organizations is GT [16].

Game theory is a mathematical analysis of interactions among rational and intelligent agents with partly or completely conflicting interests. A game is any interaction that involves two or more players which produces outcomes with respect to the preferences (or utilities) of those players. Games are categorized into cooperative games in which players focus on coalition formation, and non-cooperative games in which players do not make binding agreements as the choice or coordination of their strategies; a non-cooperative game is a more realistic representation of environmental decision making [15]. The main difference among these types is that in non-cooperative games, players make decisions independently, while in cooperative games, the basic unit of analysis is sets of players. Decision making approaches based on the GT have been widely applied in such areas as economics, biology, politics, and others [17]. Some examples of a combination of decision making methods and GT strategies are [18, 19, 20, 21, 22, 23, 24], most of them in specific applications. However, to the best of our knowledge, the problem of personnel selection has not been studied from a multi-player perspective.

In the personnel selection problem, the purpose of each decision maker is to obtain a set of N/2 candidates that are as similar as possible to those in the top positions of the ranking defined by him/her. Given that both decision makers select from the same set of candidates, there will probably be a conflict of interest as both employers will rank common candidates in their top N/2. The more similar the rankings produced by the decision makers, the greater the difference will be between the original ranking defined by the decision makers and the final subset of the candidates that will be assigned to him/her. A method based on an approach of the game theory is proposed in order to improve the personnel selection process.

This study is an innovative proposal for applying the game theory to the personnel selection problem in the context of an adversarial framework by using the rankings of candidates provided by the employers. We refer to this problem as the adversarial team selection problem.

A formalization of the problem is presented in the next section, and in section 3 the method proposed for personnel selection using a game theory approach to support employers in the process of selecting candidates is introduced.

2 Formalization of the Problem of Personnel Selection in a Competitive Multi-Player Environment

The ranking of alternatives is a common task in decision making [25]. A ranking is an ordering of a set of candidates in the personnel selection process, indicating some sort of preference relationship among the different candidates. The candidates are evaluated from multiple points of view considered relevant for the selection, and a ranking is made according to those evaluations. Every ranking can be viewed as being produced by applying an ordering criterion to a given set of objects. Let there be N candidates labelled as 1, 2, N; then, any permutation *p* of these candidates represents a ranking. Given a set of candidates, several rankings can be generated from the preferences of several decision makers; in the case of the human resources' selection problem, each employer proposes a ranking according to her/his criteria.

In this paper, we consider the following instantiation of personnel selection. Let E1 and E2 be two employers and a set of candidates $C=\{C_1, C_2, \ldots, C_N\}$, then each decision maker must select from this set of candidates N/2 members (for simplicity we assume N is even) to integrate in his/her project team. In other words, two rankings R={R1, R2} are built from C by E1 and E2 taking into account the different competences that are relevant for the different projects.

Employer E1 defines a ranking of candidates $R1=\{r_{11}, r_{12}, ..., r_{1N}\}$ and employer E2 defines another ranking $R2=\{r_{21}, r_{22}, ..., r_{2N}\}$, sorted in a decreasing order of preference, i.e., $r_{11} \geq r_{12} \geq ... \geq r_{1N}$ and $r_{21} \geq r_{22} \geq ... \geq r_{2N}$. The information about these rankings is public. The employers are now allowed to choose candidates alternatively, i.e., in turns they can choose one candidate to join their team. As there might be an overlap in the first m=N/2 candidates, i.e. $R1^*=\{r_{11}, r_{12}, \ldots, r_{1m}\}$ and $R2^*=\{r_{21}, r_{22}, \ldots, r_{2m}\}$ can be non-disjoint, there can be a conflict of interest. Actually, the greater is the similarity between the given rankings by the employers, the higher the conflict of interest. As a ranking is a permutation of N values, the similarity between rankings can be expressed using distances between permutations [26, 14]. One of the most frequently used distance measures between rankings is the Spearman footrule distance [27]. The Spearman footrule distance between two given rankings is defined as the sum over all the objects i of the absolute difference among the ranks of i with respect to the two rankings.

The first strategy is to make the selection according to the order established in the rankings R1 and R2, which is illustrated in Example 1. In Case 1, there is no conflict of interest according to R1 and R2 rankings, so that if E1 and E2 alternately choose from C according to their preferences, the resulting sets R1* and R2* fully satisfy the preferences of both employers; while in Case 2 there is definitely a conflict of interest and E2 cannot fully satisfy his/her preferences.

Example 1: Let C={1, 2, 3, 4};

Case 1: Given R1={1, 2, 3, 4} and R2={4, 3, 2, 1}, the selection results are R1*={1, 2} and R2*={4, 3}.

Case 2: Given R1={1, 2, 4, 3} and R2={3, 2, 4, 1}, the selection results are R1*={1, 2} and R2*={3, 4}.

However, in Case 2, E2 might realize that candidate 3 is not among E1's preferred candidates, and therefore instead of strictly following the order he/she communicated, E2 could follow another strategy and choose candidate 2 first. So, if E1 chooses candidate 1 first and E2 chooses candidate 2, this leads to E1 picking candidate 4 and E2 can finally choose 3; as a result we get R1*={1, 4} and R2*={2, 3} , so now E2 is the one that fully meets his/her preferences.

This new alternative approach to perform the personnel selection can be formulated as a game; the game is performed over m rounds. In each round, both of the two employers E1 and E2 select a candidate from the set of non-selected candidates according to their preference but also taking into account the preferences of the other(s). In the next section we propose a method based on the concept of a game tree to obtain the optimal strategy for both employers.

3 Decision Making Model for Personnel Selection based on a Game Theory Approach

In this section, the problem of calculating a strategy is addressed, which suggests the employers which candidate to select at each round in order to maximize their preferences.

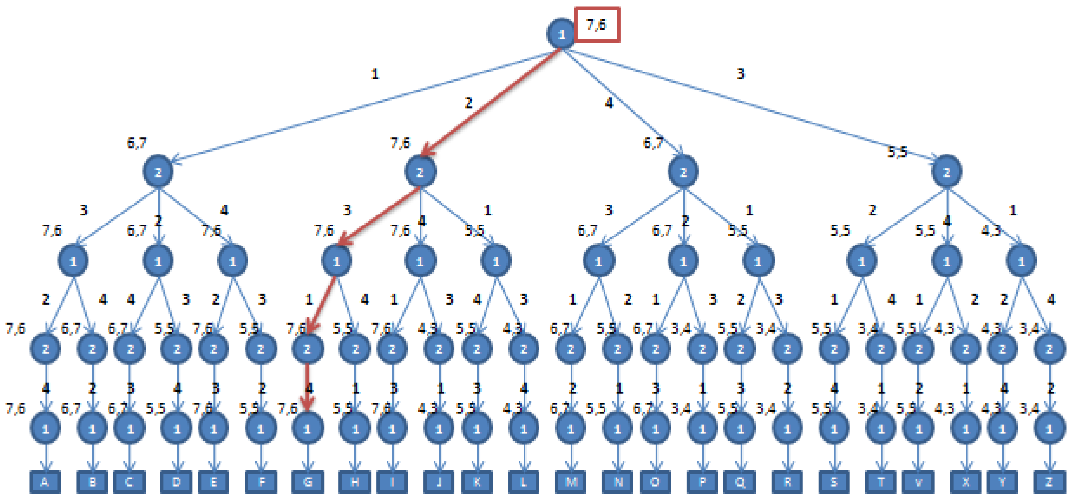
This research aims at developing an efficient decision support scheme by considering the problem as a non-cooperative game. The game consists of two players (employers) who are aware that their actions affect each other, a set of moves or actions (candidates) available to those players, and a specification of payoff for each combination strategies; each player wants to maximize his payoff by choosing the optimal set of candidates for his/her project.

The proposal is based on the approach of the extensive-form games [28], this allows the explicit representation of the sequencing of players' possible moves and their choices at every decision point; each player has information about the other player's moves when he/she makes a decision, as well as his/her payoffs for all possible game outcomes. Some elements of this representation are:

- A finite set of m (rational) players, here we consider m=2 players.
- A rooted tree, called the game tree.
- Each terminal (leaf) node of the game tree has an m-tuple of payoffs, meaning there is one payoff for each player at the end of every possible play.
- The game tree is structured in n+1 levels (n is the number of candidates).
- The complete description of the game specified by the above parameters is common knowledge among the players.

A play is thus a path through the tree from the root to a terminal node. The determination of optimal strategies is represented using a game tree; a play of a game is a path followed down the game tree. The payoff is the resulting allocation from the play of the game. A move is the selection of an action, i.e., selecting a candidate at each choice point in the game, each player can identify the moves that the opponent will make in response to each of the strategies, under the assumption that this opponent will act rationally. The game tree helps to organize and explore the impact of a decision in the future. In a 2-person game, player 1 moves at the root, player 2 moves at a resulting node on level 2, then player 1 can again selected an action, and so on. Each player can choose his/his best alternative based on his/her evaluation according to his/her preferences and the possible alternatives of the other player.

Given that, usually, the number of candidates is not too large, so we can assume that the game tree can be completely built. Each branch of the tree represents a distinct alternative to the selection of candidates, meaning each branch of the tree generates two sets: R1* and R2*, these sets can be evaluated to measure to what extent they meet the degree of preferences of every employer, which we calculate based on the well-known Borda-Kendall (BK) method [12, 29].The Borda-Kendall method is the most widely used technique for rank aggregation. For N candidates, the BK method assigns a weight N to the first



	R1* y R2*		R1* y R2*		R1* y R2*		R1* y R2*
A	{1,2}y{3,4}	G	{2,1}y{3,4}	M	{4,1}y{3,2}	S	{3,1}y{2,4}
B	{1,4}y{3,2}	H	{2,4}y{3,1}	N	{4,2}y{3,1}	T	{3,4}y{2,1}
C	{1,4}y{2,3}	I	{2,1}y{4,3}	O	{4,1}y{2,3}	V	{3,1}y{4,2}
D	{1,3}y{2,4}	J	{2,3}y{4,1}	P	{4,3}y{2,1}	X	{3,2}y{4,1}
E	{1,2}y{4,3}	K	{2,4}y{1,3}	Q	{4,2}y{1,3}	Y	{3,2}y{1,4}
F	{1,3}y{4,2}	L	{2,3}y{1,4}	R	{4,3}y{1,2}	Z	{3,4}y{1,2}

Fig.1. Personnel selection process tree game when there are four candidates and two employers

ranking place, N-1 to the second place until the weight of 1 is assigned to the last ranking place. The final rankings are determined by a weighted sum.

More formally, equation (1) is used to evaluate the set Ri* (i=1,2), where π(Cj) is the value of the candidate Cj according to its position in the corresponding ranking Ri; the function π assigns the value N to a candidate ranked first, N-1 to the second place until 1 if the candidate was ranked in the last place.

$$E(Ri^*) = \sum_{\forall Cj \in Ri^*} \pi(Cj). \qquad (1)$$

Example 2: Given the set of N=6 candidates C={1, 2, 3, 4, 5, 6} and the rankings R1={1, 2, 4, 3, 5, 6} and R2={3, 2, 6, 1, 5, 4}, the selected subsets of candidates are R1*={1, 2, 4} and R2*={3, 6, 5}. Applying expression (1) we have that E(R1*)=6+5+4=15, and E(R2*)=6+4+2=12.

Example 3: Given the set of N=6 candidates C={1, 2, 3, 4, 5, 6} and the rankings R1={1, 2, 3, 4, 5, 6} and R2={6, 5, 4, 3, 2, 1}, the selected subsets of candidates are R1*={1, 2, 3} and R2*={6, 5, 4}. Applying expression (1) we get E(R1*)=6 +5 +4=15, and E(R2*)=6 +5 +4=15. In this case, R1 and R2 rankings show that there is no conflict of interest between E1 and E2, so both sets of candidates achieved the maximum possible value according to expression (1). Here a choice strictly based on the order of preference is sufficient for both decision makers to maximize their outcomes, but it is clear that this is generally not the case.

Algorithm PS-GT (Personnel Selection based on Game Theory)

Input: Rankings R1 and R2 with N candidates set by employers E1 and E2.

Output: Sets R1* and R2* of N/2 candidates each selected by employers E1 and E2, respectively.

S1: To build the game tree with N levels.

S2: To build sets R1* and R2* for each branch in the game tree.

S3: To calculate the quality of all the sets R1* and R2* resulting from step S2, using expression (1).

S4: To assign to each leaf node a pair (v1, v2), where v1 and v2 are the quality of the sets R1* and R2*, respectively.

S5: To perform the assessment of all nodes in a bottom-up process, from the leaf nodes to the root nodes; each node is labelled with a pair (v1, v2), which corresponds to the value of the best alternative for decision makers in that level.

S6: To perform a top-down personnel selection process, that is, from the root node to a leaf node in which decision makers E1 and E2 select the best option and add it to R1* and R2*, respectively. In order to select the best option, there are considered the torque values (v1, v2) assigned to the nodes at the next level, taking the higher value of node v1 or v2 depending on whether the decision maker is E1 or E2, respectively.

End of the Algorithm

In step **S1**, all paths are generated from the root node to the leaf nodes. In odd levels (1, 3, …) it selects decision maker E1 and in even levels (2, 4, ...) it selects decision maker E2. N branches are generated from the root node, these are labelled with the corresponding N candidates in ranking R1, from the nodes in level 2, N-1 branches are generated, that is, from the N candidates in ranking R2 the candidate is excluded, who was selected at the top level by decision maker E1; from nodes at level 3 there are N-2 branches generated, i.e., the N candidates in the corresponding decision maker ranking to select, the two candidates who were selected at higher levels are excluded, i.e., the candidate selected by employers E1 and E2.

In the following game tree levels, the process is repeated, see example in Figure 1.

In step **S2**, for each branch (a path from the root node to a leaf node), sets R1* and R2* are built. In step **S3**, the quality (v1, v2) of each of these sets is calculated and assigned to the leaf nodes corresponding to step **S4**, see example in Figure 1.

In step **S5**, from the leaf nodes to the root, all node values are calculated; the employer at a particular level selects the best alternative for him/her and assigns to that node the value of that alternative. Selection of the best alternative is given by the node that is mapped with the highest value v1 (if the employer is E1) or v2 (if the employer is E2) between all pairs at that level.

In step **S6**, the selection is made from the root node to the leaf node where each employer E1 and E2 will choose the best alternative for him/her and he/she is going to add it to sets R1* and R2*, respectively.

Figure 1 shows the game tree of personnel selection process for case 2 of Example 1. The outcome of the selection process is shown in red.

4 Experimental Study

Using the game tree, the employers can decide on a good strategy in order to obtain their desired outcome to as high a degree as possible.

The purpose of this empirical study is to illustrate the proposed framework by using some examples. The effectiveness of the method based on a game approach is investigated through simulation, that is, solving some cases by using the proposed method. Below we illustrate the proposed framework by providing a trace of our algorithm on some examples. The effectiveness of our method is shown by comparing the result to the best ranked first select approach.

First case (4 candidates):

i) Given R1={1, 3, 4,2} and R2={2, 1, 3,4};

Results using the algorithm PS-GT:

R1*={1, 4}=6 and R2*={3, 2}=6.

Table 1. 4 candidates, rankings R1={1, 2, 4, 3} and R2={3, 2, 4, 1}

E2 E1	According to the order established by the rankings	Using the algorithm PS-GT
According to the order established by the rankings	R1*:{1,2} R2*:{3,4} 7,6	R1*:{1,4} R2*:{2,3} 6,7
Using the algorithm PS-GT	R1*:{1,2} R2*:{3,4} 7,6	R1*:{2,1} R2*:{3,4} 7,6

Table 2. 6 candidates, rankings R1={3, 4, 6, 1, 5, 2} and R2={3, 5, 4, 1, 6, 2}

E2 E1	According to the order established by the rankings	Using the algorithm PS-GT
According to the order established by the rankings	R1*:{3,4,6} R2*:{5,1,2} 15,9	R1*:{3,6,1} R2*:{4,5,2} 13,10
Using the algorithm PS-GT	R1*:{3,4,6} R2*:{5,1,2} 15,9	R1*:{3,6,1} R2*:{4,5,2} 13,10

Results according to the order established by the rankings:

R1*={1, 3}=7 and R2*={2, 4}= 5.

ii) Given R1={4, 1, 3,2} and R2={1, 2, 3,4};

Results using the algorithm PS-GT:

R1*={1, 4}=7 and R2*={2, 3}=5.

Results according to the order established by the rankings:

R1*={4, 3}=6 and R2*={1, 2}=7.

Second case (6 candidates):

i) Given R1={3, 2, 1, 6, 5,4} and R2={5, 2, 3, 6, 4,1};

Table 3. 8 candidates, rankings R1={1, 8, 6, 2, 3, 7, 4, 5} and R2={8, 2, 4, 5, 6, 1, 3, 7}

E2 E1	According to the order established by the rankings	Using the algorithm PS-GT
According to the order established by the rankings	R1*:{1,6,3,7} R2*:{8,2,4,5} 21,26	R1*:{1,6,3,7} R2*:{8,2,4,5} 21,26
Using the algorithm PS-GT	R1*:{8,1,6,3} R2*:{2,4,5,7} 25,19	R1*:{8,1,3,7} R2*:{2,6,4,5} 22,22

Table 4. 10 candidates, rankings R1={4, 9, 6, 7, 1, 3, 8, 2, 5, 10} and R2={7, 8, 6, 4, 1, 10, 2, 9, 5, 3}

E2 E1	According to the order established by the rankings	Using the algorithm PS-GT
According to the order established by the rankings	R1*:{4,9,6,3,2} R2*:{7,8,1,10,5} 35,32	R1*:{4,9,1,3,5} R2**:{7,6,8,2,10} 32,36
Using the algorithm PS-GT	R1*:{4,6,1,9,3} R2*:{7,8,10,2,5} 38,30	R1*:{4,6,1,9,3} R2*:{7,8,10,2,5} 38,30

Results using the algorithm PS-GT:

ii) R1*={3, 1, 6}=13 and R2*={2, 5, 4}=13.

Results according to the order established by the rankings:

R1*={3, 2, 1}=15 and R2*={5, 6, 4}=11.

It is well known from the game theory that there is an advantage for the first player (decision maker). Suppose, for example, the following extreme case. Suppose there are 6 candidates and both decision makers rank them in the same order, e.g., R1={3, 2, 1, 6, 5, 4} and R2={3, 2, 1, 6, 5, 4}. In this extreme case, decision maker 1 gets a higher outcome compared to decision

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maker 2, purely because decision maker 1 is allowed to choose first. However, in a more realistic case, the benefit of being able to choose first is less pronounced. Actually, using our approach, decision maker 2 reduces his/her disadvantage as much as possible, as he/she is playing a best response strategy, the drawback of being the second player is reduced as much as possible. In the following examples we show that the benefit of being the first decision maker is not big in general cases. Tables 1, 2, 3, and 4 illustrate the advantage of using the Game Theoretic approach (PS-GT).

In Table 1, E1 selects according to the ranking and E2 follows the game strategy. E2 obtains a better result (6 and 7, respectively), so E1 should select using the game strategy because in the other case E2 could obtain a better result.

Table 2 shows a case in which E1 always obtains the best results, but E2 could improve his/her result using the strategy.

In Table 3, E1 using the strategy obtains a better result if E2 does not use it; when E2 uses the strategies the results for both employers are the same.

Table 4 shows that E2 obtains a better result if E2 selects using the strategy and E1 selects according to the ranking, but E1 ensures the best result using the strategy.

5 Conclusions

Personnel selection is an important activity for the performance of organizations. In this paper the problem of the formation of teams was discussed where two decision makers have to form their teams from the same set of candidates. This has been called the adversarial team selection problem.

We have formulated the personnel selection problem as a non-cooperative game; the game theoretic approach provides a mathematical framework designed for the analysis of the employer interaction. The model is illustrated by presenting several numerical examples.

Experiments considering different numbers of candidates and different rankings showed that the results achieved by decision makers using the strategy based on the Game Theory ensure higher quality output than when blindly following the order established by the ranking of preferences preliminarily defined by decision makers.

This method can also be straightforwardly applied when the number of decision makers is greater than two. Let N be the quantity of candidates and K, the number of decision makers (E1, E2, …, EK); in this case, N/K is the size of each team. The game tree is built in the same way: E1 selects in the root node, E2 selects in the second level, E3 in the third level, and so on. From each branch, a team Ri*, i=1, …, K, is built; and the corresponding rankings are calculated. A vector (v1, v2, …, vK) is associated to each leaf node, where vi represents the value of the resulting set Ri*. Steps S5 and S6 are executed as in the two decision makers' case. An example of this extended scenario is the following: the Cuban Baseball League consists of 16 teams. The League has two stages, in the second stage only the best 8 teams are included. The Cuban Baseball Federation identifies the 40 best players from the rest of the teams, and the managers of the classified teams select 5 players from this set, in order to strengthen their teams.

References

1. **Kelemenis, A. & Askounis, D. (2010).** A new TOPSIS-based multi-criteria approach to personnel selection. *Expert Systems with Applications*, 37, pp. 4999–5008. DOI: 10.1016/j.eswa.2009.12.013.
2. **Lai, Y.J. (1995).** IMOST: interactive multiple objective system technique. *Journal of Operational Research Society*, Vol. 46, pp. 958–976. DOI: 10.2307/
3009907.
3. **Balezentis, A., Balezentis, T., & Brauers, W. (2012).** Personnel selection based on computing with words and fuzzy MULTIMOORA. *Expert Systems with Applications*, Vol. 39, No. 9, pp. 7961–7967. DOI: 10.1016/j.eswa.2012.01.100.
4. **Dagdeviren, M. (2010).** A hybrid multi-criteria decision-making model for personnel selection in manufacturing systems. *Journal of Intelligent Manufacturing*, Vol. 21, No. 4, pp. 451–460. DOI: 10.1007/s10845-008-0200-7.
5. **Güngör, Z., Serhadlıog˘lu, G., & Kesen, S.E. (2009).** A fuzzy AHP approach to personnel selection problem. *Applied Soft Computing*, Vol. 9,

No. 2, pp. 641–646. DOI: 10.1016/j.asoc.2008.09.003.

6. **Kabak, M., Burmaoglu, S., & Kazançoglu, Y. (2012).** A fuzzy hybrid MCDM approach for professional selection. *Expert Systems with Applications*, Vol. 39, No. 3, pp. 3516–3525. DOI: 10.1016/j.eswa.2011.09.042.
7. **Safarzadegan, S., Hassan, M., & Shahhosseini, V. (2012).** Computing with words for hierarchical competency based selection of personnel in construction companies. *Applied Soft Computing*, Vol. 12, No. 2, pp. 860–871. DOI: 10.1016/j.asoc.2011.10.004.
8. **Zhang, S., & Liu, S. (2011).** A GRA-based intuitionistic fuzzy multi-criteria group decision making method for personnel selection. *Expert Systems with Applications*, Vol. 38, No. 9, pp. 11401–11405. DOI: 10.1016/j.eswa.2011.03.012.
9. **Amit, R. & Belcourt, M. (1999).** Human resource management processes: a value-creating source of competitive advantage. *European Management Journal*, Vol. 17, No. 2, pp. 174–181. DOI: 10.1016/S0263-2373(98)00076-0.
10. **Huemann, M., Keegan, A., & Turner, J.R. (2007).** Human resource management in the project-oriented company: a review. *International Journal of Project Management*, Vol. 25, No. 3, pp. 315–323. DOI: 10.1016/j.ijproman.2006.10.001.
11. **Thomas, S. & Tang, Z. (2010).** Labour-intensive construction sub-contractors: their critical success factors. *International Journal of Project Management*, Vol. 28, No. 7, pp. 732–740. DOI: 10.1016/j.ijproman.2009.11.005.
12. **Fields, E., Okudan, G., & Ashour, O. (2013).** Rank aggregation methods comparison: A case for triage prioritization. *Expert Systems with Applications*, Vol. 40, No. 4, pp. 1305–1311. DOI: 10.1016/j.eswa.2012.08.060.
13. **Theuβl, S., Reutterer, T., & Hornik, K. (2014).** How to derive consensus among various marketing journal rankings? *Journal of Business Research*, Vol. 67, No. 5, pp. 998–1006. DOI: 10.1016/j.jbusres.2013.08.006.
14. **Zuylen, A., Schalekamp, F., & Williamson, D. (2014).** Popular ranking. *Discrete Applied Mathematics*, Vol. 165, pp. 312–316. DOI: 10.1016/j.dam.2012.07.006.
15. **Yang, M., Khan, F., Sadiq, R., & Amyotte, P. (2013).** A rough set-based game theoretical approach for environmental decision-making: A case of offshore oil and gas operations. *Process Safety and Environmental Protection,* Vol. 91, No. 3, pp. 172–182. DOI: 10.1016/j.psep.2012.05.001.
16. **Oluseyi, F. & De Wilde, P. (2010).** Dynamics of business games with management of fuzzy rules for decision making. *Int. J. Production Economics*, Vol. 128, No. 1, pp. 96–109. DOI: 10.1016/j.ijpe.2010.06.002.
17. **Castillo, L. & Dorao, C.A. (2013).** Decision-making in the oil and gas projects based on game theory: Conceptual process design. *Energy Conversion and Management*, Vol. 66, pp. 48–55. DOI: 10.1016/j.enconman.2012.09.029.
18. **Angelou, G.N. & Economides, A.A. (2009).** A multi-criteria game theory and real-options model for irreversible ICT investment decisions. *Telecommunications Policy*, Vol. 33, No. 10-11, pp. 686–705. DOI: 10.1016/j.telpol.2009.07.005.
19. **Brynielsson, J. (2007).** Using AI and games for decision support in command and control. *Decision Support Systems*, Vol. 43, No. 4, pp. 1454–1463. DOI: 10.1016/j.dss.2006.06.012.
20. **Fontanini, W. & Ferreira, P.A.V. (2014).** A game-theoretic approach for the web services scheduling problem. *Expert Systems with Applications,* Vol. 41, No. 10, pp. 4743–4751. DOI: 10.1016/j.eswa.2014.02.016.
21. **Karmperis, A.C., Aravossis, K., Tatsiopoulos, I., & Sotirchos, A. (2013).** Decision support models for solid waste management: Review and game-theoretic approaches. *Waste Management*, Vol. 33, No. 5, pp. 1290–1301. DOI: 10.1016/j.wasman.2013.01.017.
22. **Madani, K. & Lund, J. (2011).** A Monte-Carlo game theoretic approach for Multi-Criteria Decision Making under uncertainty. *Advances in Water Resources*, Vol. 34, No. 5, pp. 607–616. DOI: 10.1016/j.advwatres.2011.02.009.
23. **Reneke, J. (2009).** A game theory formulation of decision making under conditions of uncertainty and risk. *Nonlinear Analysis*, Vol. 71, No. 12. DOI: 10.1016/j.na.2009.01.154.
24. **Yanga, W. & Wanga, J. (2013).** Vague linguistic matrix game approach for multi-criteria decision making with uncertain weights. *Journal of Intelligent & Fuzzy Systems*, Vol. 25, No. 2, pp. 315–324. DOI: 10.3233/IFS-2012-0638.
25. **Hosseinzadeh, F., Rostamy-Malkhalifeh, M., Aghayi, N., Ghelej, Z., & Gholami, K. (2013).** An improved method for ranking alternatives in multiple criteria decision analysis. *Applied Mathematical Modelling*, Vol. 37, No. 1-2, pp. 25–33. DOI: 10.1016/j.apm.2011.09.074.
26. **Aledo, J.A., Gámez, J.A., & Molina, D. (2013).** Tackling the rank aggregation problem with evolutionary algorithms. *Applied Mathematics and*

Computation, Vol. 222, pp. 632–644. DOI: 10.1016/j.amc.2013.07.081.

27. **Dinu, L.P. & Manea, F. (2006).** An efficient approach for the rank aggregation problem. *Theoretical Computer Science*, Vol. 359, No. 1-3, pp. 455–461. DOI: 10.1016/j.tcs.2006.05.024.
28. **Hart, S. (1992).** Games in extensive and strategic forms. *Handbook of Game Theory with Economic Applications*, part 1.
29. **Wang, Y.M., Luo, Y., & Hua, Z. (2007).** Aggregating preference rankings using OWA operator weights. *Information Sciences*, Vol. 177, No. 16, pp. 3356–3363. DOI: 10.1016/j.ins.2007.01.008.

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