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A novel hybrid method for selecting soccer players during the transfer season

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Abstract

The quality of its players is one of the most significant features determining the failure or success of a sports team. The wide array of factors contributing to the performance of the players together with the inherent financial limitations of the clubs have transformed the selection of players into a complex problem. The current paper presents an integrated approach that combines multiple-criteria decision-making analysis and mathematical programming to support the decision maker through the building process of a soccer team. First, the fuzzy analytic network process is applied to evaluate the significance of the different performance criteria for each position in the field. The score attained by the different players in each potential position is computed using PROMETHEE II. A biobjective integer programming model has been designed to evaluate the transfer status of the players. Finally, data envelopment analysis is used to identify the most efficient Pareto solution determining the status of each player. In order to demonstrate the applicability of the proposed approach, the position in the field and transfer status of 60 players being considered by a real soccer team have been determined.

KEYWORDS

integer programming, multicriteria decision making, player selection, sports management

1 | INTRODUCTION

The increasing worldwide popularity of professional soccer has turned this sport into an expanding industry with a massive financial turnover over the past decades. In this regard, selecting the players to transfer and arranging the lineup of the team while accounting for different financial and technical constraints are fundamental factors determining the performance of a soccer team. The selection of players becomes particularly significant as their wages and transfer costs impose increasingly substantial constraints on professional soccer clubs, which must select the best potential set of players while limited by their respective budgets.

The importance of multicriteria decision making (MCDM) techniques lies in their capability to evaluate and rank alternatives across considerably different research areas (Bai, Zhang, Qian, & Wu, 2017; Guo & Zhao, 2017; Yu, Xu, & Liu, 2013). A fundamental issue regarding the application of MCDM methods is the existence of uncertainty in the relationship between the criteria and their weights (Uygun, Kaçamak, & Kahraman, 2015). The fuzzy version of the analytic network process (ANP) incorporates the relationships between criteria and subcriteria while allowing the decision makers to define realistic scenarios within uncertain environments (Ayağ & Özdemir, 2009). In addition, the structure defining the Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) II technique allows the decision makers to consider the weights of all the criteria when evaluating and ranking the alternatives (Behzadian, Kazemzadeh, Albadvi, & Aghdasi, 2010). Applying the fuzzy ANP method beforehand balances the weights of the criteria and leads to more reliable results than those derived from the direct implementation of PROMETHEE II (Kilic, Zaim, & Delen, 2015). Finally, multiobjective mathematical programming is an effective computational tool that has been consistently applied to solve selection problems in a variety of research areas.

The contribution of the current paper to the player selection literature is threefold:

- A mathematical model is proposed to solve the player selection problem while accounting for specific real-life assumptions regarding the monetary and practical aspects of soccer teams.
- The problem considered allows for players to be transferred among teams, which constitutes a completely new application of decision science to sports management.
- To the best of our knowledge, the current model provides the first application of fuzzy ANP combined with PROMETHEE to the player selection problem.

The remainder of the paper is organized as follows. Section 2 summarizes the recent literature on the selection of team members, with particular emphasis being placed on sports teams. Section 3 describes the two MCDM methods implemented in the current paper. Section 4 presents our approach to the player selection problem. In Section 5, the proposed approach is applied to a real-life case study. Section 6 concludes and suggests future research directions.

2 | LITERATURE REVIEW

In the past decades, scientific methods have been successfully applied to evaluate performance and support decision making in sport related areas. Furthermore, there is a vast literature on sports management analysing different aspects of sports teams. Similarly to management and engineering, decision making in sports can greatly benefit from incorporating scientific methods. The selection of players and lineups of a sports team is a fundamental decision for the club owners and managers when trying to achieve the best possible results (Tavana, Azizi, Azizi, & Behzadian, 2013). It is clear that the failure or success of any sports team depends on the skills of its players and the arrangement of their potential lineups. The literature on the topic of the current paper can be divided into different categories, relating mainly to sports management and engineering, and the selection and alignment of teams.

2.1 | Performance evaluation of players

The performance evaluation of players and teams is an important field of study directly related to sports teams. Casals and Martinez (2013) identified the main factors determining the performance of basketball players and presented a statistical model that analysed their relative degree of importance based on the results obtained from each game. Ballı and Korukoğlu (2014) applied a fuzzy multiattribute decision-making framework based on the fuzzy analytic hierarchy process and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to the selection problem of basketball players in Turkey. Jarvandi, Sarkani, and Mazzuchi (2013) presented a model where the skills of each player were evaluated considering their potential role in the performance of the team. Vaeyens et al. (2006) determined the relationship existing between physical factors, skill level, and the performance of young soccer players aged 12 to 16. In their study, anthropometry, maturity status, special, and sport performances among elite, subelite, and nonelite young players were all taken into account. Petrović Djordjević, Vujošević, and Martić (2015) analysed the technical efficiency of the teams competing in the World Cup using a two-level output-oriented data envelopment analysis (DEA) method.

The valuation of players performed in sports management and engineering studies has been employed as an instrumental factor in the selection of players. Kedar-Levy and Bar Eli (2008) designed a model that calculated the value of players considering factors such as their future performance uncertainty and the potential arrangements introduced by their coach. They estimated the expected performance of each player and the overall one of the team using conventional regression models. Duch, Waitzman, and Amaral (2010) aimed at determining how to define quantitative values for the personal characteristics of the soccer players competing in UEFA's European Championship. They developed a network method that quantified the contributions of individual players to the overall performance of the team. These authors also claimed that their executive method could be generalized and applied to other research areas in order to improve the overall performance of any team.

2.2 | Player selection

It is widely acknowledged that team selection is a factor of considerable relevance in project management research. In this regard, Karsak (2000) presented a multiobjective fuzzy programming model to identify the qualitative factors determining the selection of personnel when trying to fulfil a set of qualitative goals. de Korvin, Shipley, and Kleyle (2002) developed a multiphase project model that recognized the skills necessary in each phase of the project to select the appropriate personnel for a given budget constraint. Their algorithm used a compatible fuzzy structure to measure the ratio of each person's skills to the necessary skills in each phase of the project. Shipley and Johnson (2009) also introduced a model based on a fuzzy structure to select and recruit an appropriate team while considering the skills required by and goals of the project. Feng, Jiang, Fan, and

Fu (2010) proposed a method to select the members of a cross-functional team. These authors focused on the effect that the performance of each member had both on the performance of the team and that of the other members, that is, their collaborative performance. They also presented a multiobjective 0–1 programming model and an improved NSGA-II algorithm to solve the resulting NP-hard problem.

Within a sports-related environment, Hu, Zhou, Zhang, and Zhao (2015) developed a DEA approach to rank and select sports coaches, Mirabile and Witte (2015) designed a model for selecting the players of a university soccer team, and Qader et al. (2017) applied MCDM and statistical methods to a football player selection problem.

2.3 | Position assignment

Gerrard (2001) proposed a method to define the lineup of professional sports teams using qualitative criteria obtained from features that became evident during their performance. Dežman, Trninić, and Dizdar (2001) validated experimentally a decision-making system to determine the positions and roles of basketball players more efficiently. Boon and Sierksma (2003) designed a multicriteria model to optimize the lineup of a team based on the abilities of the players and the constraints imposed by soccer and volleyball settings. Frick (2007) reviewed the literature on the transfer of soccer players and summarized the main factors determining the salaries of players and their transfers costs in Europe. Gil, Ruiz, Irazusta, Gil, and Irazusta (2007) focused on the physical factors and effective physical conditions determining the selection of soccer players.

Trninić, Papić, Trninić, and Vukičević (2008) analysed the evolution of the role of the position in group sports, ultimately requiring players to be aware of multiple technical and tactical details through the game. As a result, the roles of players have become much more dynamic depending on the style and conditions of the game together with the position of the ball and that of their teammates and the players of the opposite team. These authors designed a three-phase model to determine the potential of the different players in their selection for a particular position. Kavi (2012) optimized the arrangement of the tactical system and the game in a soccer match using real data and an integer programming model. Tavana et al. (2013) introduced a two-phase framework to select the players and determine the lineup. In the first phase, the players were evaluated using a fuzzy ranking method based on the highest efficiency of the team. In the second phase, the different potential lineups were evaluated through a fuzzy inference system, and the best one was chosen. Bonomo, Durán, and Marenco (2014) defined the lineup of virtual soccer teams for each round of the Argentinian League using two mathematical programming models. The first model selected the appropriate lineup for a game, whereas the second optimized the lineup selected together with a tactical system.

As can be inferred from the above review of the literature, several studies have analysed the problem of lineup arrangement in sports teams, but none of them has considered the selection of players during the transfer season while allowing for their lending and borrowing across teams. As will be emphasized throughout the empirical analysis, the subjective intuition of the coach and the technical staff, together with the existence of managerial pressures, play a substantial role in the selection of players during the transfer season. Despite the increasing budgetary importance of the process, consistently highlighted in the media (Christenson & Fenn, 2018), formal MCDM methods remain mainly unused. The intuition for this fact follows from the existence of private interests and exogenous factors, other than purely efficiency-based ones, determining the decisions made among the teams composing the main world leagues. As a result, teams competing in the second and third divisions are the ones that may need to focus more on the efficiency and optimality of their choices and must therefore rely on a formal MCDM framework such as the one presented in the current paper.

3 | THE PROPOSED APPROACH

The approach presented in this study is composed by two different MCDM methods, namely, fuzzy ANP and PROMETHEE II, together with a biobjective mathematical programming model. A brief description of both MCDM methods is provided in Appendix A.

Several factors are determinant when forming a soccer team that aims at fulfilling the expectations of the club. These factors include quantitative criteria, such as profit, and qualitative ones like stamina, speed, passing ability, and ball control. In addition, the role and responsibilities of each player, which range from defending against opponent attacks to scoring, are directly associated with his/her position in the soccer field. The positions considered in this paper are illustrated in Figure 1.

In the first phase of our approach, the factors determining the performance of the players in each position are weighed using the fuzzy ANP method. This has been done to account for the relative importance displayed by each criterion when considering the different positions within the field. In the second phase, several experts evaluate the players using the PROMETHEE II method. In the third and final phase, we present a mathematical model in which the score assigned to each player through PROMETHEE II is used to define one of its objective functions and the other relates to the potential profits and losses resulting from the transfers. The structure of the suggested model is presented in Figure 2.

3.1 | The proposed fuzzy ANP structure

A wide array of methods has been implemented in the literature when dealing with multicriteria evaluation and decision-making problems. The ANP method is generally applied when considering complicated conceptual frameworks dealing with many factors that the decision maker has to evaluate simultaneously. The ANP overcomes the resulting complexity by requiring the decision maker to perform pairwise comparisons across the set of factors. The use of pairwise comparisons allows for the aggregation of two-factor evaluations instead of forcing the decision maker to

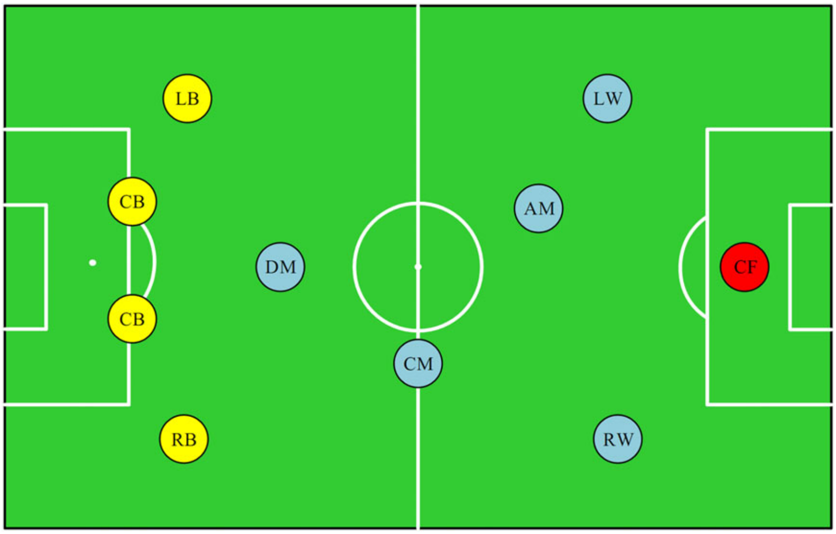

FIGURE 1 Location of the soccer positions in the field

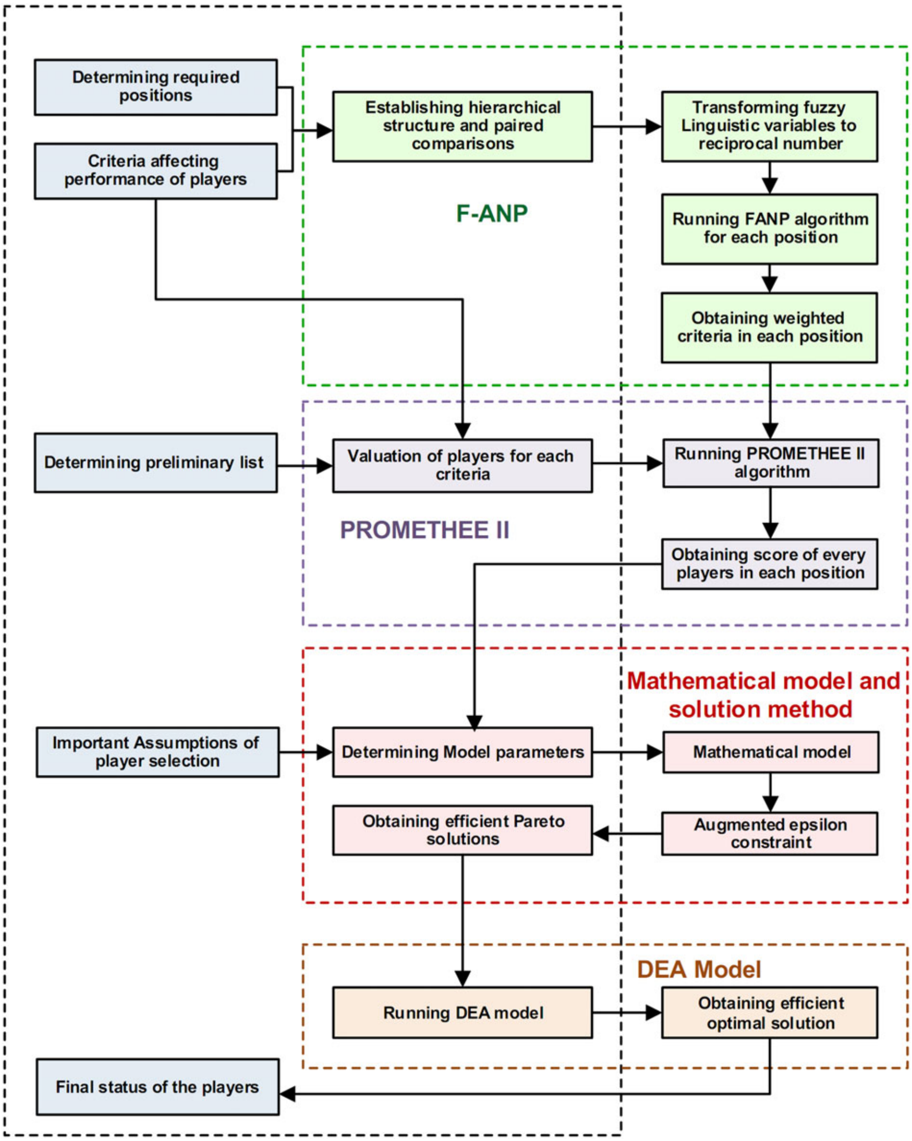

FIGURE 2 Proposed framework

perform a simultaneous comparison of many factors, which constitutes a much more difficult cognitive exercise. At the same time, the ANP considers the interrelationships existing among the factors, increasing the accuracy of the results obtained (Coulter & Sarkis, 2006), while allowing for the integration of qualitative/intangible and quantitative/tangible measures into a single overall score to rank the decision alternatives. The integration of fuzzy logic within the ANP framework in order to deal with the uncertainty inherent to the data improves its performance. Thus, fuzzy ANP is used in the current paper to weight the criteria selected.

The criteria and subcriteria considered to be important by the experts and the literature when evaluating players are presented in Table 1. The existing relationships among the different criteria are described in Table 2 and Figure 3. In order to weigh the criteria used in the selection of players via fuzzy ANP, a standard questionnaire was submitted to a group of experts.

3.2 | Implementation of PROMETHE II

The value $\phi(a)$ described in Appendix A is derived from the PROMETHE II algorithm using the weights of each j criterion (w_j) obtained in Subsection 3.1. The different alternatives considered for each position p are denoted by the index i. That is, PROMETHE II is applied to determine the score of each player i in each potential position p. Hereafter, the notation φ_{ip} will be used instead of $\phi(a)$ when defining the mathematical model in the next step of our approach.

3.3 | Mathematical model

In the second phase of the proposed approach, a mathematical programming model is defined to complete the selection process of soccer players. Because clubs generally experience constraints regarding transfers, we have developed a set of assumptions that take into account near real-life conditions. These assumptions are described as follows:

- The number of players assigned to the different positions is determined by coaches and experts.
- The decision regarding the transfer of players can either be permanent or a temporal loan.
- The club benefits from transferring a player whose contract has not expired, whereas a fee is charged for buying or borrowing a player from outside the club.
- There should not be more than one star player (i.e., a very famous and exceptionally talented player) per position because, otherwise, a star player would remain on the bench.
- Some players can be assigned to several positions with different probabilities that are calculated in their final score.
- The standard rule regarding the maximum number of foreign players applies.

TABLE 1 Criteria and subcriteria for player selection

Cluster	Main criteria	Subcriteria	Reference
C_1	Goal	Weight of each criterion in position p	
C_2	Technical ability	Passing	(Tavana et al., 2013)
		Ball control	
		Heading	
		Free kick	
		Finishing	
		Tackling	
		Dribbling	(Tavana et al., 2013; Vaeyens et al., 2006)
		Shoot	
		Moving without the ball	
		Crossing	
C_3	Mental ability	Environmental awareness	(Miller, Roberts, & Ommundsen, 2005; Mills, Butt, Maynard, & Harwood, 2012; Tavana et al., 2013)
		Team working	(Miller et al., 2005; Mills et al., 2012)
		Self-confidence	
		Environmental adaptability	
		Read the game	(Mills et al., 2012; Tavana et al., 2013)
		Creativity	
C_4	Physical ability	Great stamina	(Gil, Gil, Ruiz, Irazusta, & Irazusta, 2007; Tavana et al., 2013)
		Jumping	
		Speed	(Tavana et al., 2013)
		Power	(Gil et al., 2007)
		Reaction	
		Both feet	(Tavana et al., 2013)
		Injury rate	(Hägglund, Waldén, Bahr, & Ekstrand, 2005; Hawkins, Hulse, Wilkinson, Hodson, & Gibson, 2001; McCall et al., 2014)

TABLE 2 Relationship between subcriteria

Independent criteria	Dependent criteria
Passing	Creativity Read the game Reaction speed Both feet
Ball control	Creativity Both feet Reaction speed
Dribbling	Ball control Creativity Environmental awareness Speed Reaction speed Both feet
Shoot	Power Both feet Creativity
Injury rate	Power Great stamina
Heading	Jumping Power
Moving without the ball	Creativity Environmental awareness Read the game Great stamina
Free kick	Creativity Shoot Crossing Both feet
Crossing	Both feet
Finishing	Shoot Reaction speed Creativity Self-confidence
Tackling	Reaction speed

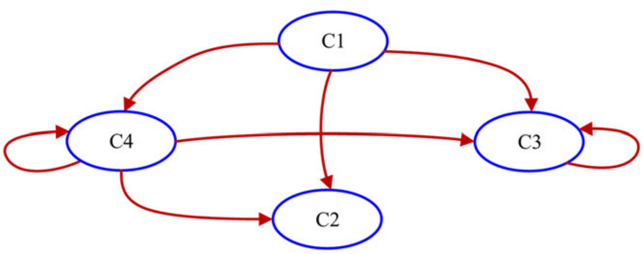

FIGURE 3 Proposed network structure

- The selection process is performed for all the position considered by the coach except the goal-keeper one.
- There are 24 players in a soccer team. Thus, excluding the three goalkeepers, a total of 21 players must be selected.
- There is a budget limit on the expenses.
- The team coaches select and arrange the main nine positions depending on the game strategy being implemented.

3.3.1 | Indices and sets

i the index identifying the players

p the index used for the position

A set of all the players (inside and outside the team)

B set of players available for purchase

S set of players available for sale

L set of players available for loan from other teams

L' set of players available for loan to other teams
F set of foreign players
TP set of top players who should always play in case they are selected

3.3.2 | Parameters

φ_{ip} score of player i in position p (obtained from PROMETHE II)
PTF_i primary cost for buying player i
FTF_i expected income received from selling player i at the end of the period
TR_i current selling price of player i
c_i cost of loaning player i
$Budget$ primary budget of the club for the transfer season
ρ_{ip} probability of aligning player i in position p
λ_p the number of players required for position p (both starting lineup and substitutes)
τ_p number of players required for position p in the starting lineup
δ_{ip} 1 if player i is assigned to position p, 0 otherwise
θ number of foreign players allowed in the team
α interest rate
M a large number

3.3.3 | Decision variables

X_{ip} 1 if player i in position p is purchased from another team,
1 if player i in position p is owned by the team and not to be sold,
0 otherwise
Y_{ip} 1 if player i in position p is borrowed from another team,
1 if player i in position p is owned by the team and not to be lent,
0 otherwise
U_{ip} 1 if player i in position p is placed on the team list, 0 otherwise
V_i 1 if player i is placed on the team list, 0 otherwise

3.3.4 | Mathematical programming model

$$Max\ Z_1 = \sum_{p=1}^{m} \sum_{i \in A} \rho_{ip}\varphi_{ip}V_i, \tag{1}$$

$$Max\ Z_2 = \sum_{i \in S}\left[(TR_i - FTF_i(e^{-\alpha}))\left(1 - \sum_{p=1}^{m} X_{ip}\right)\right] - \sum_{i \in B}\left((PTF_i - FTF_i(e^{-\alpha}))\sum_{p=1}^{m} X_{ip}\right).- \sum_{i \in S}\left(c_i \sum_{p=1}^{m} Y_{ip}\right) \tag{2}$$

St.

$$U_{ip} = (X_{ip} + Y_{ip})\delta_{ip} \quad \forall i \in (B \cup L),\ \forall p, \tag{3}$$

$$U_{ip} = (X_{ip} + Y_{ip} - 1)\delta_{ip} \quad \forall i \in \left(S \cup L'\right),\ \forall p\,, \tag{4}$$

$$\sum_{p=1}^{m} U_{ip} = V_i \quad \forall i \in A\,, \tag{5}$$

$$\sum_{i \in B}\left(PTF_i \sum_{p=1}^{m} X_{ip}\right) - \sum_{i \in S}\left[TR_i\left(1 - \sum_{p=1}^{m} X_{ip}\right)\right] + \sum_{i \in L}\left[c_i\left(1 - \sum_{p=1}^{m} Y_{ip}\right)\right] \le Budget, \tag{6}$$

$$\sum_{p=1}^{m} \sum_{i \in A} U_{ip} = 21, \tag{7}$$

$$\sum_{p=1}^{m} \sum_{i \in F} U_{ip} \le \theta, \tag{8}$$

$$\sum_{i \in A} \delta_{ip} U_{ip} \ge \lambda_p \quad \forall p, \tag{9}$$

$$U_{ip} \le \tau_p \delta_{ip} + \left(1 - \delta_{ip}\right) \quad \forall i \in TP, \forall p, \tag{10}$$

$$\sum_{p=1}^{m} \left(X_{ip} + Y_{ip}\right) \ge 1 \quad \forall i \in \left(S \cap L'\right), \tag{11}$$

$$\sum_{p=1}^{m} \left(X_{ip} + Y_{ip}\right) \le 1 \quad \forall i \in (B \cap L), \tag{12}$$

$$\sum_{p=1}^{m} Y_{ip} = 1 \quad \forall i \in \left(S - L'\right), \tag{13}$$

$$X_{ip} \le \delta_{ip} \quad \forall i \in A, \forall p, \tag{14}$$

$$Y_{ip} \le \delta_{ip} \quad \forall i \in A, \forall p, \tag{15}$$

$$Y_{ip} = 0 \quad \forall i \in (B - L), \forall p, \tag{16}$$

$$X_{ip} = 0 \quad \forall i \in (L - B), \forall p, \tag{17}$$

$$X_{ip}, \quad Y_{ip}, \quad U_{ip}, \quad V_i \in (0, \; 1) \quad \forall i \in A, \forall p. \tag{18}$$

3.3.5 | Model description

Equation (1) is the first objective function of the model and seeks to maximize the expected score derived from each player by considering the probability of assigning him/her to the different positions available. Note that, even though each player has a preferred position assigned, it is possible to align him/her in different positions under particular circumstances. Therefore, when evaluating the players, their scores across all potential positions should be considered along with the probability of aligning them in the corresponding positions. Thus, in order to compute the comparative score of each player, we multiply the probability of assigning a player to each position, ρ_{ip}, by his/her score in the corresponding position, φ_{ip}.

Equation (2) is designed to maximize the net present value derived from the transfers of players. The first term accounts for the profit obtained from selling the players owned by the team before the end of the period. The second term considers the costs of the players being transferred during the transfer season, that is, at the beginning of the period. Finally, the costs derived from the players on loan are included in the third term.

Note that $e^{-\alpha}$ has been used to discount future cash flows to the beginning of the period. In other words, $e^{-\alpha}$ incorporates the time value of money when calculating the value of each player at the end of the period via FTF_i. That is, $e^{-\alpha}$ is used instead of $\frac{1}{1+\acute{\alpha}}$, with the relationship between $\acute{\alpha}$ and α described as follows:

$$e^{-\alpha} = \frac{1}{1+\acute{\alpha}} \quad \rightarrow \ln e^{-\alpha} = \ln\left(\frac{1}{1+\acute{\alpha}}\right) \quad \rightarrow \alpha = \ln(1+\acute{\alpha}).$$

A clear trade-off exists between both objective functions, that is, the higher the quality and, consequently, the score of a player, the higher his/her buying or selling price. The model should therefore aim at balancing both objectives given the set of constraints described below.

Constraint (3) is designed to select a player from the set of those available for purchase or on loan based on their quality within a given position. In other words, Constraint (3) determines which players should be bought or borrowed from other teams during the transfer season. If either X_{ip} or Y_{ip} equals 1 for player i in position p, then he/she will be either purchased or borrowed and considered for the corresponding position. Similarly, Constraint (4) determines whether players stay in the team or are either sold or lent to another team. If either X_{ij} or Y_{ij} equals 1 for player i in position p, he will not be sold or lent but considered for the corresponding position in the team. Constraint (5) integrates the results from both previous constraints and defines the set of players composing the team list, that is, it calculates the value of the variable V_i, which is used in the first objective function. Constraint (6) is the primary budget constraint conditioning the number of transfers. Constraint (7) represents for the total number of players whom the team can own within a season. Constraint (8) limits the number of foreign players composing the team. Constraint (9) guarantees the amount of players required by a given position. Constraint (10) states that the top players are constantly part of the starting lineup of the team. Constraint (11) prevents a player from being sold and loaned at the same time. Constraint (12) prevents a player from being simultaneously bought and borrowed. Constraint (13) implies that only those players available for lending are actually lent to other teams. Constraints (14) and (15) guarantee that players are assigned to a position based on their expertise. Constraints (16) and (17) limit the transfers of players so that the players available for purchase cannot be loaned and vice versa. Constraint (18) defines the binary variables considered in the model.

3.4 | Augmented epsilon constraint

The epsilon constraint method identifies a subset of the Pareto set that solves the optimization problem. More precisely, this method selects one of the objective functions as the main one to be optimized, while remaining objective functions are considered as constraints. The main advantage of the epsilon constraint method is that it is capable of obtaining efficient solutions in a nonconvex Pareto curve. However, the precision of the results obtained is highly dependent on the value of the ε_i upper bounds imposed exogenously. Therefore, the method is not efficient when facing a large number of objective functions. Mavrotas (2009) developed an improved version of the epsilon constraint method (i.e., the augmented ε-constraint) leading to more efficient Pareto solutions. The augmented ε-constraint method is described below.

Consider an optimization problem with j objective functions $f_j(x)$, $j = (1, 2, \ldots, k)$. The mathematical form of the ε-constraint method is presented in Equation (19)

$$\begin{aligned} &Min\, f_j(x), \quad j = (1, 2, \ldots, k) \\ &s.t. \quad f_i(x) \leq \varepsilon_i, \quad \forall i \in (1, 2, \ldots, k),\, i \neq j;\, X \in S. \end{aligned} \tag{19}$$

Clearly, the solution derived from Equation (19) is optimal if the values of the slack or surplus variables associated to all the other objective functions are equal to zero. Considering this requirement, the augmented ε-constraint model is described in Equation (20)

$$\begin{aligned} &Min\, f_j(x) + \beta \times (s_i), \quad i = (1, 2, \ldots, j-1, j+1, \ldots, k) \\ &s.t. \quad f_i(x) + s_i = \varepsilon_i, \quad \forall i \in (1, 2, \ldots, j-1, j+1, \ldots, k);\, X \in S, \end{aligned} \tag{20}$$

where $\beta \in [0.000001, 0.001]$ is a randomly chosen parameter that solves the model. The augmented ε-constraint model presented in Equation (20) delivers only efficient Pareto solutions. In order to make the objective functions commensurable, it is preferable to use Equation (21),

$$Min\, f_j(x) + \beta \times \left(\frac{s_i}{r_i}\right), \quad j = (1, 2, \ldots, j-1, j+1, \ldots, k), \tag{21}$$

where r_i $(i = 1, 2, \ldots, j-1, j+1, \ldots, k)$ denotes the range of the ith objective function value, which is obtained using the payoff table from the corresponding single objective optimization of the original model.

After solving the proposed mathematical model using the augmented ε-constraint method, DEA is applied to the Pareto results obtained so as to determine the optimal efficiency of all the potential candidates.

3.5 | Data envelopment analysis

DEA is an MCDM technique that calculates the efficiency of decision-making units (DMUs) by considering their respective sets of input and output variables. DEA models are generally categorized as either input or output oriented. In the output-oriented models, the efficiencies of the DMUs are obtained by maximizing outputs while considering inputs as constants. In this regard, the objective functions defined in Equations (1) and (2) are both treated as output variables because we are aiming at maximizing them.

Thus, an output-oriented DEA model is utilized to calculate the efficiency scores of the Pareto front. Moreover, a dummy variable will be incorporated as an input to the DEA environment. The model presented in Equation (22) corresponds to an output-oriented DEA setting that evaluates the relative efficiencies of n DMUs $(j = 1, 2, \ldots, n)$ using m inputs to produce s outputs (Charnes, Cooper, & Rhodes, 1978).

$$
\begin{aligned}
& Max\ \theta \\
& s.t. \quad x_{ip} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1, \ 2, \ \ldots, \ m \\
& \qquad \theta y_{rp} \leq \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1, \ 2, \ \ldots, \ s \\
& \qquad \lambda_j \geq 0 \qquad\qquad j = 1, 2, \ldots, n\,.
\end{aligned} \tag{22}
$$

A known drawback of the model presented in Equation (22) is that it is likely to rank more than one DMU as efficient, requiring modifications to be able to identify the most efficient DMU among the efficient ones. Thus, we have applied the modified version of the above DEA model introduced by Andersen and Petersen (1993) and described in Equation (23).

$$
\begin{aligned}
& Max\ \theta \\
& s.t. \quad x_{ip} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1, \ 2, \ \ldots, \ m \\
& \qquad \theta y_{rp} \leq \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1, \ 2, \ \ldots, \ s \\
& \qquad \sum_{j=1}^{n} \lambda_j = 1 \\
& \qquad \lambda_j \geq 0 \qquad\qquad j = 1, \ 2, \ \ldots, \ n\,.
\end{aligned} \tag{23}
$$

4 | PRACTICAL APPLICABILITY

As discussed in the previous sections, the current paper aims at providing a decision support tool for team lineup arrangement. As a result, real-world functions of football clubs regarding standard transactions are allowed for, and teams can buy, sell, lend, and borrow players. These decisions are made by a club while constrained by different financial and operational aspects. That is, a team lineup must attain the best potential results and the transactions of players lead to satisfactory financial gains or, at least, to the reduction of costs and expenses.

Therefore, the main practical applicability of the current research consists of providing a tool that improves the capacity of decision makers to select the most appropriate players for the positions determined by the coaching team. The input data used to select the players composing the premilinary list being considered include the opinions of talent finders, coaches, and managers of the team. At first, the players proposed by the talent finders are monitored, and the required information collected. Then, given the management strategy of the club and the analysis derived from the information collected by the coaches, the best transfer plan can be obtained using the current approach.

It should be highlighted that the opinion of talent finders as well as their interactions with coaches and managers could be formally assumed to determine the players composing the preliminary list. In this regard, these interactions could be modelled through a fuzzy ANP setting and used to complement the analysis performed in the current paper. However, as already emphasized, several additional features ranging from marketing and strategic considerations to purely subjective judgements would have a direct effect on the selection process. This would complicate the problem at hand considerably while increasing the volatility of the results obtained as a result of the exogenous nature of many of these new constraints.

The proposed model is a comprehensive mathematical tool that can be used to evaluate players, reduce the role played by sheer intuition (which is generally subjective and can yield disastrous results), and, if properly implemented, eliminate nepotism (which is largely exercised in the sport arenas of some countries). Despite these advantages, we acknowledge the fact that players cannot be treated as mere scores and that many of their qualities can only be managed through the perspective and experience of a coach. For example, players can improve their capabilities and evolve through time. Also, if assigned to the appropriate position together with certain matched coplayers, they can perform considerably better. Furthermore, though professionalism consists of delivering a certain level of performance regardless of the situation, psychological factors, and the subjective perception of the players regarding the set of teams, coaches, and other players can modify their performance drastically.

Finally, it should be emphasized that the purchase of a player generally takes place through a bidding process where different teams compete in the payments offered to the players. Therefore, no matter how sophisticated the proposed method is, we still cannot rely on it completely. The technical staff and the coach remain in charge of the decision processs, though computer-based support methods should become common practice when dealing with particularly complicated scenarios.

4.1 | Case study

In order to demonstrate the applicability of the proposed methodology, a real Iranian team, namely, the Toran[1] soccer club, has been used as a case study. It should be reminded that goalkeepers are not considered in our approach due to the special attributes of their position. Therefore, 10 players form the starting lineup and a total of 21 players must be evaluated when accounting for the substitute ones. According to the coaching

[1]The name has been changed to protect the anonymity of the team.

team, 10 main positions are considered for Toran, that is, two CB players and one player for each of the other positions in the starting lineup. All positions require a total of two players except for CM and CB, which require three and four players, respectively.

In the initial phase of the evaluation process, soccer experts gathered the necesary data through a standard ANP questionnaire. The linguistic evaluations retrieved were converted into fuzzy numbers using a scale such as the one described in Appendix A. In order to provide further intuition, the results obtained from the fuzzy pairwise comparisons for the middle-defence position are presented in Appendix B. In addition, the

TABLE 3 Weights obtained after evaluating the criteria for each position

Subcriteria	CB	RB	LB	DM	CM	AM	RW	LW	CF
Environmental awareness	0.0791	0.0291	0.0291	0.0500	0.0367	0.0285	0.0167	0.0167	0.0475
Read the game	0.0838	0.0259	0.0259	0.0415	0.0230	0.0243	0.0142	0.0142	0.0184
Self-confidence	0.0552	0.0074	0.0074	0.0219	0.0236	0.0110	0.0171	0.0171	0.0637
Environmental adaptability	0.0242	0.0028	0.0028	0.0171	0.0116	0.0068	0.0083	0.0083	0.0029
Creativity	0.0467	0.0684	0.0684	0.0825	0.1324	0.1226	0.1810	0.1810	0.1569
Team working	0.0276	0.0156	0.0156	0.0254	0.0045	0.0118	0.0000	0.0000	0.0000
Both feet	0.0109	0.1185	0.1185	0.0493	0.0635	0.0764	0.0982	0.0982	0.0469
Great stamina	0.0640	0.0795	0.0795	0.0921	0.0669	0.0593	0.0247	0.0247	0.0531
Power	0.1475	0.0424	0.0424	0.0855	0.0758	0.0606	0.0377	0.0377	0.0639
Jumping	0.0853	0.0015	0.0015	0.0305	0.0175	0.0170	0.0038	0.0038	0.0296
Speed	0.0863	0.0465	0.0465	0.0298	0.0320	0.0177	0.0113	0.0113	0.0233
Reaction speed	0.1445	0.1637	0.1637	0.1388	0.1488	0.1313	0.0955	0.0955	0.0903
Injury rate	0.0486	0.0210	0.0210	0.0437	0.0294	0.0224	0.0014	0.0014	0.0118
Dribbling	0.0000	0.0405	0.0405	0.0261	0.0465	0.0514	0.0762	0.0762	0.0300
Finishing	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0444	0.0444	0.0610
Moving without the ball	0.0158	0.0528	0.0528	0.0355	0.0192	0.0386	0.0370	0.0370	0.0616
Ball control	0.0210	0.0822	0.0822	0.0726	0.0885	0.0952	0.1159	0.1159	0.0651
Passing	0.0162	0.0579	0.0579	0.0591	0.0663	0.0720	0.0578	0.0578	0.0459
Crossing	0.0035	0.0584	0.0584	0.0038	0.0167	0.0197	0.0416	0.0416	0.0006
Free kick	0.0014	0.0187	0.0187	0.0091	0.0319	0.0267	0.0149	0.0149	0.0015
Shoot	0.0003	0.0079	0.0079	0.0182	0.0415	0.0491	0.0822	0.0822	0.0800
Tackling	0.0210	0.0516	0.0516	0.0443	0.0236	0.0384	0.0000	0.0000	0.0000
Heading	0.0169	0.0079	0.0079	0.0234	0.0000	0.0193	0.0202	0.0202	0.0458

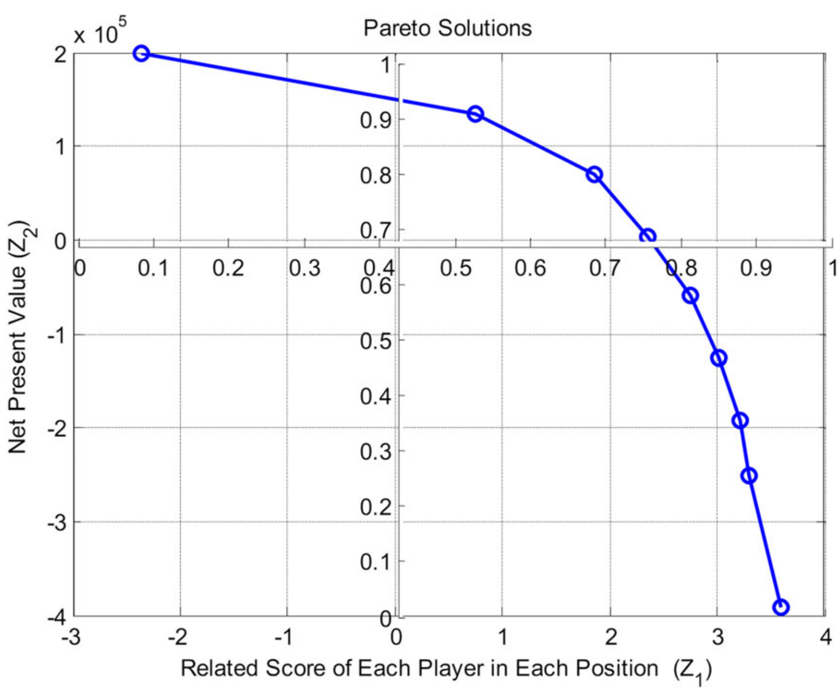

FIGURE 4 Pareto solutions obtained using the augmented ε-constraint method

TABLE 4 Value of the objective functions for the Pareto solutions obtained

Optimal point	Relative score of each player in each position (Z_1)	Net present value (Z_2)
1	3.588	−391,859.045
2	3.303	−250,245.396
3	3.303	−250,245.396
4	3.215	−191,639.330
5	3.020	−125,533.805
6	2.751	−59,026.7640
7	2.354	2,679.41000
8	1.849	70,335.5310
9	0.741	133,642.355
10	−2.371	199,148.855

TABLE 5 Efficiency scores of the Pareto solutions

Pareto solution	Efficiency score
1	1.002
2	1.012
3	1.036
4	1.038
5	1.045
6	1.043
7	1.131
8	1.158
9	1.093
10	1.006

weighted supermatrices used to perform comparisons for this and all the other positions are presented in supporting information (Appendix C) together with the set of pairwise comparison matrices composing the fuzzy ANP model.

The final weights derived from the fuzzy ANP phase after evaluating the criteria for each position are applied to assess the players through PROMETHEE II. The ANP-based weights are presented in Table 3, and the final scores of each player resulting from the PROMETHEE II algorithm (φ_{ip}) are described in Table D1 within supporting information (Appendix D).

The biobjective mathematical model proposed to select 21 players out of the 60 suggested ones for nine different field positions is then solved using the augmented ε-constraint method. The values of the input parameters, including φ_{ip}, used when solving the mathematical model are provided in supporting information (Appendix D), whereas the Pareto-optimal solutions obtained are presented in Figure 4 and Table 4.

TABLE 6 List of players acquired or borrowed by the club

Player	Position	*PTF*	*FTF*	c	Transfer type
1	CB	25,000	20,000	-	Purchase
8	RW	10,000	20,000	-	Purchase
10	CB	11,000	21,000	-	Purchase
12	RB	20,000	8,000	-	Purchase
13	DM	10,000	15,000	-	Purchase
15	AM	8,000	5,000	-	Purchase
16	RW	30,000	32,000	-	Purchase
18	CF	42,000	26,000	-	Purchase
25	LW	62,000	92,000	-	Purchase
30	RB	70,000	100,000	52,000	Purchase
32	CM	32,000	12,000	10,000	Borrow
35	RW	98,000	120,000	75,000	Purchase
37	CB	10,000	13,000	3,000	Purchase
41	CM	110,000	137,000	75,000	Purchase
42	AM	43,000	56,000	20,000	Purchase

TABLE 7 Status of the players owned by the club

Player	Position	*TR*	*FTF*	Status
44	RW	24,000	14,000	Sale
45	CF	20,000	32,000	Stay with the team
46	CB	68,000	79,000	Sale
47	LB	11,000	28,000	Stay with the team
48	RB	15,000	9,000	Sale
49	DM	3,000	38,000	Stay with the team
50	CM	20,000	20,000	Stay with the team
51	AM	12,000	19,000	Sale
52	LW	6,500	21,000	Sale
53	RW	15,000	18,000	Sale
54	CF	7,000	17,000	Sale
55	CB	20,000	28,000	Stay with the team
56	LB	16,000	42,000	Stay with the team
57	RB	33,000	74,000	Leave on loan
58	DM	10,000	12,000	Sale
59	CM	23,000	44,000	Sale
60	AM	88,000	104,000	Sale

After retrieving the set of Pareto-optimal points, DEA is applied to identify and select the most efficient one. The results derived from applying DEA to the Pareto solutions obtained in the previous phase are presented in Table 5.

As can be observed, Pareto solution #8 is the most efficient one given the objective functions being considered. The final status of the players both owned by and added to the team is described in Tables 6 and 7. These results provide the coaching team with all the information required to optimize their lineup and transfer decisions.

The optimal results described in these tables imply that a total of 15 players should be added to the team during the transfer season. One of these players should be borrowed from outside the club, whereas the other 14 should either be bought from other teams or have their contracts extended if they were about to expire. The results obtained also indicate that 11 players should leave the team during the transfer season. One of these players should be lent, whereas the other 10, who currently have a contract with the team, should be sold. The positive net present value of the objective function for the eight optimal point described in Table 4 implies that the club can acquire additional technically qualified players while simultaneously maximizing profits.

5 | CONCLUSION

The selection process of players performed while considering the different requirements and constraints faced by a team together with the worldwide set of available alternatives is a real challenge for any professional soccer club. The current paper has defined a decision support method to help building a soccer team through the selection of players during the transfer season. The proposed method uses fuzzy ANP to weight the criteria requirements of the different field positions and computes the position suitability of each player through PROMETHEE II. In addition, a biobjective mathematical model was proposed to maximize the total score of the players selected while minimizing the transfer costs being incurred. After deriving the set of Pareto-optimal solutions, DEA was applied to determine the most efficient scenario based on the objectives considered by the decision maker. The results obtained help determining the set of players that should be purchased or loaned from other teams and whether the players whose contracts have not yet expired should remain in the team or be sold, or loaned, to other teams. The results derived from the model indicate that the scientific support of decisions during the transfer season can yield positive returns to the team and facilitate its success. Future studies may consider multiperiod models or applying the proposed approach to the selection of players in other team sports.

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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APPENDIX A

MCDM METHODS

A.1 | Fuzzy ANP Method

The ANP is an MCDM method defined by Saaty (2001) as an extension of the AHP to account for interactive effects among criteria and the effects of subcriteria on criteria. In other words, ANP is used to model non-linear hierarchical relationships. The general structure of the ANP network is presented in Figure A1. The reader is referred to Saaty (2001) for additional information on the ANP method.

The ANP model is extended to a fuzzy environment, Zadeh (1965), through the fuzzy linguistic scale described in Table A1, which is used to weigh the criteria employed in the selection of players. Moreover, the numerical equivalent of the experts' opinions when performing fuzzy pairwise comparisons across criteria is obtained using Table A1 (or, equivalently, Figure A2). It should be noted that, when performing pairwise comparisons, the inverse of a number is inserted in its reciprocal position within the matrix. The same is true for fuzzy pairwise comparisons described via triangular fuzzy numbers (TFNs).

The next step consists of deriving the weighted and limit supermatrices, which reveal important information about the relative priority of the criteria.

We describe below how fuzzy theory can be applied to the ANP method using the extent analysis of Chang (1996).

Consider two triangular fuzzy numbers, namely, $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$, such as those illustrated in Figure A3. Standard mathematical operations defined on M_1 and M_2 follow

$$M_1 + M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \tag{A1}$$

$$M_1 \otimes M_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2), \tag{A2}$$

$$M_1^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right), \quad M_2^{-1} = \left(\frac{1}{u_2}, \frac{1}{m_2}, \frac{1}{l_2}\right) \quad M_1 \neq 0 \text{ and } M_2 \neq 0. \tag{A3}$$

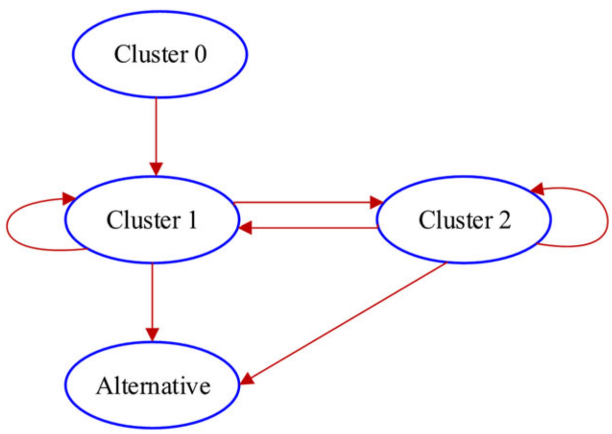

FIGURE A1 General analytic network process network structure

TABLE A1 Fuzzy linguistic scale for importance

Linguistic scale for importance	Triangular fuzzy reciprocal scale	Triangular fuzzy scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important (ED)	(2/3, 1, 2)	(1/2, 1, 3/2)
Weakly more important (WMD)	(1/2, 2/3, 1)	(1, 3/2, 2)
Strongly more important (SMD)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)
Very strongly more important (VSMD)	(1/3, 2/5, 1/2)	(2, 5/2, 3)
Absolutely more difficult (AMD)	(2/7, 1/3, 2/5)	(5/2, 3, 7/2)

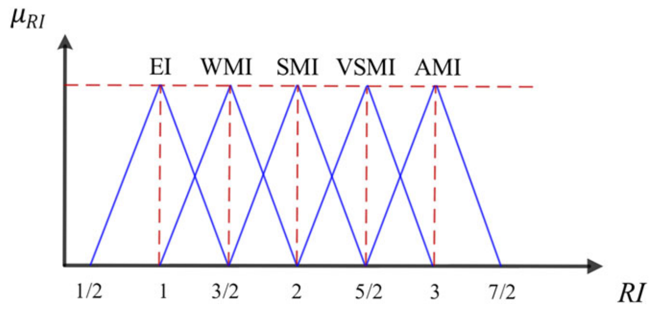

FIGURE A2 Linguistic scale for relative importance (RI)

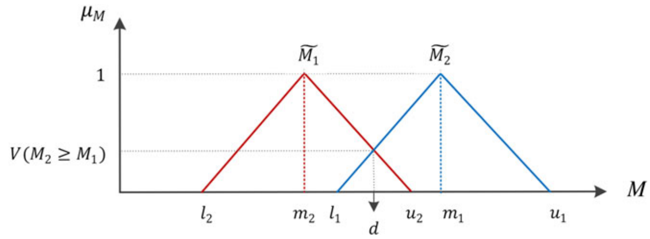

FIGURE A3 Obtaining $(M_2 \geq M_1)$ for triangular fuzzy numbers M_1 and M_2 when $m_1 \geq m_2$

Let $X = \{x_1, x_2, ..., x_n\}$ denote an object set and $G = \{g_1, g_2, ..., g_n\}$ a goal set. Following Chang (1996), m extent values can be defined per object and goal, g_i, as follows.

$M_{g_i}^1, M_{g_i}^2, ..., M_{g_i}^m \qquad i = 1, 2, ..., n,$

where all the $M_{g_i}^j$, $j = 1, 2, ..., m$, are TFNs.

Considering i and j as indexes for the alternatives and criteria, respectively, the steps of the algorithm can be described as follows:

Compute the value of S_i, which is a fuzzy synthetic extent defined for the ith alternative as

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1}. \tag{A4}$$

In order to calculate $\sum_{j=1}^{m} M_{g_i}^j$ and $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1}$, we apply formulas (A5) and (A6), respectively:

$$\sum_{j=1}^{m} M_{g_i}^j = \sum_{j=1}^{m} l_{ij}, \sum_{j=1}^{m} m_{ij}, \sum_{j=1}^{m} u_{ij}, \tag{A5}$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} m_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} l_{ij}} \right). \tag{A6}$$

The degree of possibility of $M_1 \geq M_2$, denoted by $V(M_1 \geq M_2)$, is equal to 1 if and only if $m_1 \geq m_2$. On the other hand, the possibility of $M_2 \geq M_1$ is calculated using the formula

$$V(M_2 \geq M_1) = \sup_{y \geq x} \left[\min \left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right], \tag{A7}$$

whose numerical value can be obtained via

$$V(M_2 \geq M_1) = hgt(M_2 \cap M_1) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases}. \tag{A8}$$

As Figure A3 illustrates, point d is located at the intersection of the two triangles defined by the membership functions μ_{M_1} and μ_{M_2}.

The possibility of a convex fuzzy number being larger than $k$convex fuzzy number(s) is defined using

$$V(M \geq M_1, M_2, ..., M_k) = V[(M \geq M_1) and (M \geq M_2) and ... and (M \geq M_k)] = \min V(M \geq M_i), \qquad i = 1, 2, ..., k. \tag{A9}$$

Given this definition, the following weight vector can be calculated:

$$W' = \left(d'(A_1), d'(A_2), ..., d'(A_n)\right)^T, \tag{A10}$$

where

$$d'(A_i) = \min V(S_i \geq S_k) \qquad for \ \ k = 1, 2, ...n; \ k \neq i. \tag{A11}$$

Finally, the weight vector defined in (A10) must be normalized.

$$W = (d(A_1), d(A_2), ..., d(A_n))^T, \tag{A12}$$

where W is a nonfuzzy number.

A numerical example illustrating how fuzzy theory can be applied to the ANP is provided by Chang (1996).

A.2 | PROMETHEE II Method

PROMETHEE and TOPSIS are two of the main methods commonly used in the MCDM literature to rank sets of alternatives (Mardani et al., 2015), with an important branch of the literature arising from the different versions of the former (Behzadian, Kazemzadeh, Albadvi, & Aghdasi, 2010). It should be noted that, when tested empirically, both these methods display substantial similarities in their respective rankings (Bevilacqua Leoneti, 2016).

PROMETHEE II provides a complete ranking of a given finite set of alternatives determined via pairwise comparisons across criteria. More precisely, alternatives are evaluated using a set of criteria that must be either maximized or minimized. The implementation steps of PROMETHEE II (an extension of the PROMETHEE I MCDM method defined by Brans & Vincke, 1985) are the following ones:

The difference between alternatives, d_j, is derived via pairwise comparisons. In particular, $d_j(a, b)$ is used to denote the existing difference between alternatives a and b for criterion j.

$$d_j(a, b) = g_j(a) - g_j(b), \tag{A13}$$

where g_j defines the evaluation of alternatives based on criterion j.

$p_j(a, b)$ is calculated using an appropriate preference function F_j.

$$p_j(a, b) = F_j[d_j(a, b)] \quad j = 1, 2, ..., k. \tag{A14}$$

$p_j(a, b)$ defines the strength of the preference for a over b when considering criterion j and $d_j(a, b)$.

The weighted sum of the preference values, that is, the global preference index $\pi(a, b)$, is computed via

$$\pi(a, b) = \sum_{j=1}^{k} p_j(a, b) w_j \quad \forall a, \ b \in A, \tag{A15}$$

where w_j represents the weight of criterion j. In the current paper, the values of w_j are obtained through the ANP.

The positive, $\phi^+(a)$, and negative, $\phi^-(a)$, outranking flows associated to the ratings of each alternative are calculated.

$$\phi^+(a) = \frac{1}{n-1} \sum_{i \in A} \pi(a, i), \tag{A16}$$

$$\phi^-(a) = \frac{1}{n-1} \sum_{i \in A} \pi(i, a). \tag{A17}$$

The positive and negative flows are added.

$$\phi(a) = \phi^+(a) - \phi^-(a), \tag{A18}$$

and the net flow for each alternative is finally obtained.

As can be inferred from the above steps, two main components of the analysis must be defined in order to implement this method, namely, the weights of the corresponding criteria and the preference function per criterion. This latter function converts the evaluation differences between two alternatives into a preference degree that ranges from zero to one. We implement the usual criterion preference function defined by Brans and Vincke (1985), which is defined as follows:

$$F_j[d_j(a,b)] = \begin{cases} 0 & d_j \le 0 \\ 1 & d_j > 0 \end{cases}, \quad j = 1, 2, \ldots, k. \tag{A19}$$

APPENDIX B

FUZZY ANP TABLES

TABLE B1 Pairwise comparison matrix for mental ability in goal

Mental ability	Environmental awareness	Read the game	Self-confidence	Environmental adaptability	Creativity	Team working
Environmental awareness	(1, 1, 1)	(1/2, 1, 3/2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(3/2, 2, 5/2)
Read the game	(2/3, 1, 2)	(1, 1, 1)	(1, 3/2, 2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)
Self-confidence	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 1, 1)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 3/2, 2)
Environmental adaptability	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1, 1, 1)	(1, 1, 1)	(1/2, 1, 3/2)
Creativity	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1, 1, 1)	(1, 1, 1)	(1, 3/2, 2)
Team working	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(2/3, 1, 2)	(1/2, 2/3, 1)	(1, 1, 1)

TABLE B2 Pairwise comparison matrix for physical ability in goal

Physical ability	Both feet	Great stamina	Power	Jumping	Speed	Reaction speed	Injury rate
Both feet	(1, 1, 1)	(1/2, 2/3, 1)	(2/7, 1/3, 2/5)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(2/5, 1/2, 2/3)
Great stamina	(1, 3/2, 2)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1/2, 1, 3/2)
Power	(5/2,3, 7/2)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 1, 3/2)	(3/2, 2, 5/2)
Jumping	(2, 5/2, 3)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1, 1, 1)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)
Speed	(2, 5/2, 3)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(1, 1, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)
Reaction speed	(2, 5/2, 3)	(1, 3/2, 2)	(2/3, 1, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 1, 1)	(2, 5/2, 3)
Injury rate	(3/2, 2, 5/2)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1, 1, 1)

TABLE B3 Pairwise comparison matrix for the effective criteria in passing

Passing	Environmental awareness	Read the game	Creativity
Environmental awareness	(1, 1, 1)	(2/3, 1, 2)	(1/2, 2/3, 1)
Read the game	(1/2, 1, 3/2)	(1, 1, 1)	(1/2, 2/3, 1)
Creativity	(1, 3/2, 2)	(1, 3/2, 2)	(1, 1, 1)

TABLE B4 Pairwise comparison matrix for the main criteria in goal

Goal	Mental ability	Physical ability	Technical ability
Mental ability	(1, 1, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)
Physical ability	(1, 3/2, 2)	(1, 1, 1)	(3/2, 2, 5/2)
Technical ability	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1, 1, 1)