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Multi-Objective Optimization for Football Team Member Selection

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ABSTRACT Team composition is one of the most important and challenging directions in the recommendation problem. Compared with a single person, the advantage of a team is mainly reflected in the synergy of team members' complementary collaboration. To build a high-efficiency team, how to choose the team members has become a tricky problem. However, there is a lack of quantitative algorithms and validation methods for team member selection. In this paper, we put forward three indicators to measure a team's ability and formulate the selection of football team members as a multi-objective optimization problem. Subsequently, an evolutionary player selection algorithm based on the genetic algorithm is proposed to solve the team composition problem. We verify the effectiveness of the team member recommendation algorithm via data analysis, football game simulation under different budget constraints and provide comparisons with existing methods.

INDEX TERMS Team composition, multi-objective optimization, genetic algorithm.

I. INTRODUCTION

Teamwork is the collaborative effort of a team to accomplish a common destination or to complete a shared task in the most effective and efficient way. Compared with a single person, a team can integrate not just knowledge but skills of each member from different professional domains reasonably based on their characteristics. Teamwork can solve problems with complementary advantages and realize the value-added benefit of $1 + 1 > 2$, which is critical for achieving common goals. However, it is very difficult for us to form a team that covers all aspects of knowledge and skills needed, hence automatically recommending a team with high competitiveness, by defining some indicators according to existing experiences and studying quantitative algorithms, is in great necessity.

Football has become one of the most popular sports in the world. At the same time, football is highly inherently cooperative, so football team composition is greatly representative of the studying of the team composition problem. In reality, evaluating the effectiveness of football team composition is nearly impossible. However, fortunately, with the recent development and progress of electronic games, we can study the football team composition problem by simulating virtual football video games. In recent years, many football video games with high authenticity and reliability have been developed in the game market, such as Federation International Football Association (FIFA),[1] Pro Evolution Soccer (PES),[2] and Football Manager (FM).[3] Such video games can assess players' attribute values precisely according to the real abilities of those players on the pitch, which provides great convenience for our research and verification, see the game interface of PES2021 in Fig. 1. Moreover, take Electronic Arts[4] as an example, it is a famous interactive entertainment software company in the world, which publishes the FIFA game series every year. Through the official website https://sofifa.com/, we can obtain professional official ratings of more than 10,000 football players, such as players' salaries and nationalities. It has some advantages in the research of team composition, such as high timeliness, full characteristics, and rich content. Fig. 2 illustrates some official data of the legendary football player *Lionel Messi*.

The team member composition problem is quite different from the general single-objective optimization problem,

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[1]https://www.fifa.com/
[2] https://www.konami.com/
[3]https://www.footballmanager.com/
[4]https://www.ea.com/

FIGURE 1. Football game interface of the PES2021 game platform.

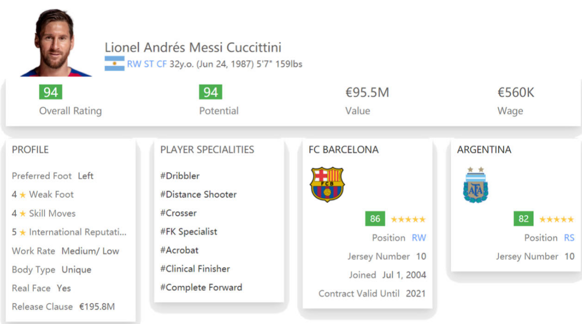

FIGURE 2. Player profile of Lionel Messi.

which has only one specific objective to optimize. However, the team composition is often affected by multiple aspects, which makes the evaluation become very subjective and vary with personal preferences, hence the simple optimization methods and recommendation algorithms failed in this scenario. But fortunately, we can measure the ability of a team through various evaluation indicators, which are then turning into different objectives by considering different aspects of team members. By optimizing different objective functions, we simplify the practical team member composition problem into a multi-objective optimization problem, which can be solved by established techniques.

In this paper, we conduct a specific and comprehensive study on the topic of the team member recommendation problem. We first define some conceptions that are useful for elaborating our novel indicators, and then adopt modified Non-dominated Sorting Genetic Algorithms-II (NSGA-II) to compose a high-quality football team in terms of winning rate. Finally, we implement the proposed method and evaluate it through the simulation of the football video game PES2021. We list the main contributions as follows:

- We define three indicators to evaluate the performance of football players, which contribute to a novel framework for team composition.
- We formulate the team composition problem as a novel multi-objective optimization function, and propose a modified genetic algorithm named Evolutionary Selection of Players (ESP) to solve it.
- We evaluate the proposed model via numerical analysis, game simulation based on the Pro Evolution Soccer 2021 (PES2021) platform, and comparison with other classical approaches.

The remainder of this paper is organized as follows. Section II introduces the latest progress of the recommendation system and its application in the field of sports team composition, as well as the literature review of multi-objective optimization methods. We propose three indicators for evaluating players and football teams in Section III. In Section IV, we model the team member composition problem as a multi-objective optimization problem and propose a modified genetic algorithm named ESP to solve it. We conduct comprehensive experiments to validate the effectiveness of our proposed ESP algorithm through data analysis and game simulation in Section V. Section VI compares our proposed model and the corresponding algorithm with others. Finally, we conclude our work, discuss the shortages and give some future directions in Section VII.

II. RELATED WORK

A. TEAM RECOMMENDATION IN SPORTS FIELD

The research on recommendation systems can be traced back to the mid-1990s. Its main application is to recommend items or services to users based on their similar preferences, known as collaborative filtering. Recommendation system plays a pivotal role in online shopping, e-commerce services, and social network applications. In recent years, there has been a wide range of practical issues covering researches and developments in the field of recommendation. For example, Ayata *et al.* [1] proposed an emotion-based music recommendation framework that learns user emotions from wearable physiological sensor signals. Sun and Zhang [2] integrated techniques in dialog systems and recommender systems into a novel and unified deep reinforcement learning framework. Furthermore, Strub *et al.* [3] enhanced the hybrid recommender systems based on Autoencoders. However, few studies have applied related conceptions and technologies of recommendation systems to the problem of football team member composition, let alone the automatic team composition applied in the field of electronic virtual football video games.

On recommendation for sports, Qader *et al.* [4] proposed a method for evaluating and ranking football players based on multi-criteria decision-making, where players were selected according to several physical fitness indicators, such as 30-meter speedrunning. Similarly, Di Salvo *et al.* [5] investigated performance characteristics according to skill positions of elite soccer players. In the study, they argued that different positions have different physical requirements for players. In [6], Özceylan adopted the Analytic Hierarchy Process (AHP) algorithm, which is a structured technique for group decision making, combined with 0-1 integer programming method, to select players. Kamble *et al.* [7] also applied the AHP algorithm to select cricket players. Despite the popularity of the AHP, many authors have explored some other heuristic methods for player selection. In [8], Ahmed *et al.* utilized the NSGA-II algorithm to select players, but the definition of the objective function is subjective, and there is no reliable verification method to prove the effectiveness of the algorithm. Grund [9] exploited the density of network data structure, taking the Premier League football team as an example, to study the team performance. However, if the network structure is used to connect players in the same team for player recommendation, there will be a problem that all players cannot be connected by each other, i.e., the player graph is not connected. Besides, a fuzzy inference system is also adopted into player selection [10], but this method largely depends on the experiences and cognitive abilities of experts. Zeng *et al*. [11] hashed over a skill coverage function by using the submodule optimization technique, which selects players by maximizing the constructed skill coverage function. Nevertheless, the constructed function still has some shortcomings, e.g., the skill coverage of a team will reach a maximum as long as one player has a very high score on a certain attribute, no matter how other players perform. Besides, it is not suitable to predict players' salaries based on the fitted exponential function which only considers the performance-price ratio of players.

Team composition is often more than a temporary consideration. For example, on the football field, player transactions and contracts would not expire within four years. Therefore, the potentials of team members are of great importance. Teams with greater potentials tend to achieve higher valuations and better long-term performance. There are a variety of literature on the field of evaluating potentials of football players. E.g., Williams and Reilly [12] attempted to integrate their main research findings with talent identification and development in soccer. Similarly, Unnithan *et al*. [13] did research on talent identification in youth soccer. In [14], Jimǹez and Pain explored the relative age effect in Spanish Association football and provided a comprehensive elaboration on the influence of player ages.

However, in the studies mentioned above, the indicators of selecting players are subjective and lacking quantitative evaluation. The subjective player selection methods cannot be verified by numerical approaches. Besides, those methods only focus on football players' physical fitness, ignoring the comprehensiveness of the composed group. Furthermore, those researchers did not consider the potential of the composed team, i.e., the future performance of the team, which is of great importance.

B. MULTI-OBJECTIVE OPTIMIZATION METHODS

Multi-objective optimization methods have been widely used in many areas, including engineering and economics where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. In the past decades, numerous studies have attempted to solve multi-objective optimization problems (MOPs). Among them, evolutionary algorithm (EA) is one of the mainstream algorithms. Many researches have been carried out, including ant colony algorithm [15], genetic algorithm and particle swarm optimization [16], [17]. Particularly, MOEA/D, an acronym for multi-objective evolutionary algorithm based on decomposition, provides a new idea for solving MOPs [18]. Inspired by MOEA/D, some decomposition-based algorithms are also proposed [19]–[21]. Furthermore, evolutionary algorithms also provide new ways for solving practical problems. For example, Li and Yin [22] used differential evolutionary algorithm to design a reconfigurable antenna array with quantized phase excitations. In [23], a multi-search differential evolutionary algorithm with self-adaptive parameter control was proposed for solving global real-parameter optimization problems. Additionally, several heuristic optimization algorithms have also been explored to deal with the MOPs. For instance, Li *et al*. [24] proposed a new heuristic optimization method, called animal migration optimization algorithm. The algorithm is inspired by animal migration behavior, which is a ubiquitous phenomenon that can be found in all major animal groups. Besides, Li *et al*. [25] put forward a new multi-objective forest algorithm that can identify protein-RNA interactions from CLIP-seq data. This study provides a refreshing insight into the use of multi-objective optimization for genome informatics.

In addition to the MOPs, many of the previous researches on dynamic multi-objective optimization problems (DMOPs) [26]–[28], which focuses on the multiple conflicting goals that change over time, have also been explored. For example, Xu *et al*. [27] proposed a cooperative co-evolutionary strategy based on environmental sensitivities for solving DMOPs. Furthermore, Rong *et al*. [26] put forward a multi-directional prediction strategy to enhance the performance of EAs for DMOPs.

In this paper, we focus on the genetic algorithm, one of the pivotal methods in EAs, which aims to balance different objective functions as well as find the solution set that makes each objective function as optimal as possible. Among several multi-objective genetic algorithms, NSGA [29] is one of the most influential and widely used ones, and has been improved by Deb *et al*. [30]. The improved one is called NSGA-II. Due to the simplicity and effectiveness, the NSGA-II algorithm has successfully been applied in various fields [31]–[33].

Based on the relationship between football players and teams, we propose three indicators to evaluate the ability of a team. Besides, we construct the team composition problem as a novel multi-objective optimization function, which will be resolved by a new modification of NSGA-II algorithm and we further verify the effectiveness of our proposed model and algorithm by simulating virtual video game.

III. ESTABLISHMENT OF EVALUATION INDICATORS

In this section, we design three indicators to evaluate the performance of teams and football players, which contribute to a novel framework for team composition. The reason why we consider the three indicators will be discussed in Section V in detail.

A. OVERALL EVALUATION OF PLAYERS AND TEAMS

Given a football player P_i, the most important factor for team composition is the player's ability, which we define as the overall evaluation $\phi_{\text{Overall}}(P_i)$. It is a comprehensive property based on the player's general performance in a football game. The overall evaluation of a player considers different football skills, including the players' physical attributes, football technology, and psychological quality. We integrate the overall evaluations of all football players in a team to form the team ability, which is defined as $\phi_{\text{Overall}}(N)$, where N is the total number of football players in a team. The specific calculation method can be seen in Eq. (1).

$$\phi_{\text{Overall}}(N) = \sum_{i=1}^{N} \phi_{\text{Overall}}(P_i) \tag{1}$$

B. OFFENSIVE AND DEFENSIVE ABILITY OF PLAYERS

It is not enough to form a competitive football team only based on a player's overall evaluation, which will evoke some shortcomings. For example, if the selected players are all forwards, it will make the team's defensive ability insufficient.

As we have analyzed above, there is a significant difference in soccer players' abilities at different positions on the field. When measuring the ability of a forward, we require more offensive skills, such as control and speed of the ball and shooting skills. Similarly, when considering the ability of a guard, we desire higher defensive attributes such as physical contact ability. Taking the famous football star *Messi* as an example, his ability in an offensive position is generally higher than that in a defensive position, so it will be sensible to put this player in the offensive position.

In this paper, we consider the football players' abilities for different positions, and divide the positions except for *Goalkeeper* into three parts: *Attack* position (e.g. Striker, Center Forward), *Midfield* position (e.g. Center Midfield) and *Defensive* position (e.g. Center Back). *Attack* position describes a player's offensive ability, while *Defensive* position measures the player's defensive attribute. Besides, we consider both offensive and defensive abilities for the *Midfield* position because of its position specialty.

For a soccer player P_i, we use $\lambda_{\text{Atk}}(P_i)$ and $\lambda_{\text{Def}}(P_i)$ to represent a player's offensive ability for *Attack* position and defensive score for *Defensive* position respectively, and λ_{GK} refers to a player's goalkeeping attribute. The calculation method of a player's offensive ability is the average score of his abilities in different offensive positions (and similar applies to the measure of defensive ability). We adopt the following method to compute them:

$$\begin{cases} \lambda_{\text{Atk}}(P_i) = Mean(\mu_{\text{St}}, \cdots, \mu_{\text{Cam}}) \\ \lambda_{\text{Def}}(P_i) = Mean(\mu_{\text{Cb}}, \cdots, \mu_{\text{Cdm}}) \end{cases} \tag{2}$$

where μ represents the player's performance in different positions. For example, μ_{St} shows the player's performance in the *Striker* (St). Similarly, μ_{Cam} is the player's performance in the *Center attack midfield* (Cam). Since there are as many as 26 positions on the pitch, to save space, readers may refer to the website https://sofifa.com/ for more specific abbreviations.

C. PLAYER POTENTIAL

The two factors mentioned above are based on the current situation, but if we want the result of team composition to be effective, workable, and sound, it must be grounded in the present and the future as well. For a football player, we describe future ability as the potential attribute. However, how to measure the potential value of players in a team is a difficult problem. According to the analysis of the players' data, we found that the characteristics associated with the potential value of players are players' age, current performance, and so on. Given a player P_i, we use $Po(P_i)$ to represent his potential value, which consults the comprehensive evaluation results of football scouters in the dataset.

IV. TEAM COMPOSITION AS A MULTI-OBJECTIVE OPTIMIZATION PROBLEM

As previously asserted, building a football team with a high winning rate requires many considerations, including the overall evaluation of the team, the offensive, and defensive abilities of the players, as well as the potential value. In this section, we model the team composition as a multi-objective optimization problem based on the three factors proposed in Section III. We first formulate the football team composition problem, and then elaborate on the algorithm for selecting players.

A. MODEL FORMULATION

We formulate the team composition problem as a multi-objective optimization problem based on a series of optimization parameters. Given a football player P_i, let $S(P_i)$ represent the player's salary, and B be the team's total budget, the multi-objective optimization problem can be formulated as follows:

$$\begin{aligned} max & \begin{cases} \sum_{i=1}^{N} & \phi_{\text{Overall}}(P_i) \\ \sum_{i=1}^{N} & Po(P_i) \\ \sum_{j=1}^{N_{\text{players}}} & \lambda_{\text{Atk}}(P_j) \\ \sum_{j=1}^{N_{\text{players}}} & \lambda_{\text{Def}}(P_j) \\ \sum_{k=1}^{N_{\text{GK}}} & \lambda_{\text{GK}}(P_k) \end{cases} \\ s.t. & \sum_{i=1}^{N} S(P_i) \leqslant B \end{aligned} \tag{3}$$

where N_{players} is the total number of football players in three positions (i.e. *Attack* position, *Midfield* position, and *Defensive* position) and N_{GK} is the number of goalkeepers. The parameters N, N_{players} and N_{GK} are all constants. Particularly in our case, we have $N_{\text{players}} = 10$, $N_{\text{GK}} = 1$, and $N = N_{\text{players}} + N_{\text{GK}} = 11$. Indeed, the proposed model formulated in Eq. (3) can be extend to a matchday team with reserves or an entire team. For example, when considering the bench players, we can adjust the total number of football players N as needed.

Note that we formulate the team composition problem as a multi-objective optimization shown in Eq. (3). In the single-objective optimization problem, we can easily determine the superiority of a solution over other solutions by comparing their objective function values. However, for the multi-objective optimization problem, the result is a set of solutions that achieves the best trade-off between competing objectives, and the goodness of a solution can be obtained by the Pareto dominance [34].

B. ESP ALGORITHM

There exists multiple Pareto optimal solutions for multi-objective optimization, and evolutionary algorithms fundamentally operate on a set of candidate solutions, thus we focus on genetic algorithms, which is one of the major evolutionary algorithm paradigms, for further solving the optimization problem. In this section, we elaborate on the ESP algorithm, which is a modification of NSGA-II. We first provide a brief description of the NSGA-II procedure [30] and then illustrate the ESP algorithm in detail.

Fig. 3 shows the general procedure of NSGA-II. The basic flow of NSGA-II algorithm is similar to the traditional genetic algorithm, including critical components such as coding, crossover, mutation, and selection. Besides, NSGA-II explores three special characteristics (i.e., fast non-dominated sorting approach, density estimation and crowded-comparison operator). Specifically, according to the criteria for the sorting process, NSGA-II first initializes a random parent population. The population is sorted based on the non-domination. Once the first sorting is completed, the usual binary tournament selection, recombination, and mutation operators are used to create an offspring population, which is then combined with the current generation population. Followed by the combination procedure, NSGA-II introduces the elitism criterion to compare the current population with the previous best solutions and selects the individuals of the next generation based on the crowded-comparison operator.

Based on the multi-objective player selection optimization model, the ESP algorithm absorbs the advantages of NSGA-II and some modification is done to make it better fit the need for the football player selection problem. Specific changes are explained from the following two aspects.

1) CODING METHOD

In the genetic algorithm NSGA-II, the individual variables of each generation are usually continuous. However, we make each variable of individual as an integer representing the serial number of each player. Besides, the length of a chromosome is set to 11, which equals the number of football players. Considering there is only one goalkeeper in a team, we choose the first bit of the chromosome limited to the goalkeeper selection and the remaining 10 bits of a chromosome represent non-goalkeeper players.

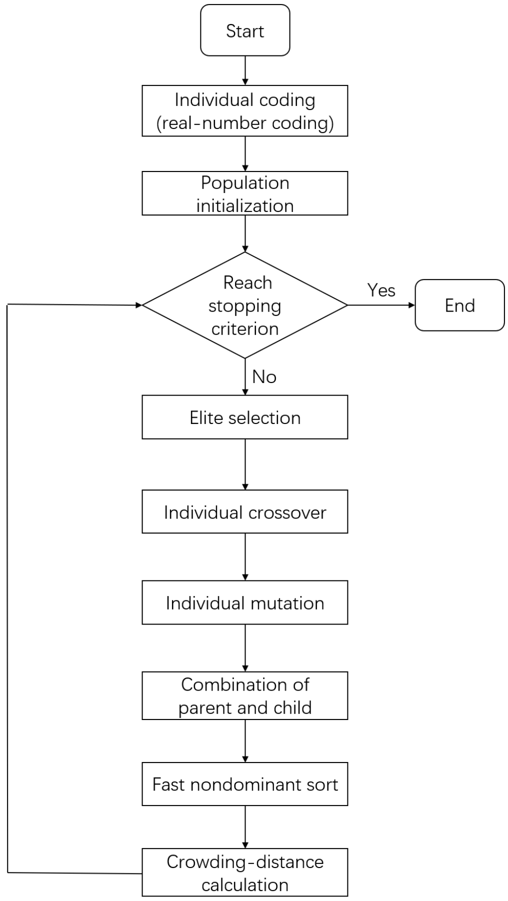

FIGURE 3. The flowchart of the NSGA-II algorithm.

TABLE 1. A toy example of the chromosome reordering process.

Type of the Chromosome	The Serial Number										
Initial	8	133	6	7	12	23	61	1	3	30	4
Rearranged	8	1	3	4	6	7	12	23	30	61	133

In addition, we also arrange the remaining 10 bits of the chromosome in ascending order according to the serial number, which represents the player's salary (see Table 1). The smaller the value of the serial number, the higher the player's salary. During the cross recombination procedure, rearranging the similar chromosome sequence makes a small difference in salary between the two players, and avoids meaningless updating operations. Furthermore, it can better control the total cost of the team and reduce the probability of non-feasible solutions.

2) FAST NON-DOMINATED SORTING PROCESS BASED ON BUDGET CONSTRAINTS

It is not an easy task to solve the team composition problem with budget constraints. In the ESP algorithm, we introduce a variable *Constraint Violation* (CV) in Eq. (4) to make the final solution satisfy the budget constraint.

$$CV = max\left(0, \frac{TC - B}{B}\right) \tag{4}$$

where TC is the total cost of the team. Based on the above formula, the constraint violation value of a feasible solution is always 0, while the one for the non-feasible solution is greater than 0. The larger the violation value, the greater the deviation of the non-feasible solution.

By introducing the concept of the constraint violation, we change the rules of the fast non-dominated sorting process, which is the key component of the NSGA-II algorithm. Given any two solutions (i.e. individuals in the population) x_a and x_b, of which decision values are $a \triangleq CV(x_a)$ and $b \triangleq CV(x_b)$ respectively, the new dominant relationship is obtained as follows:

- If $CV(x_a) = 0$ and $CV(x_b) > 0$, we have a dominates b, or otherwise, b dominates a.
- If $CV(x_a) > 0$ and $CV(x_b) > 0$, we have the smaller CV dominates the larger CV.
- If $CV(x_a) = 0$ and $CV(x_b) = 0$, the dominant relationship is determined according to the rules mentioned in Pareto dominance.

Algorithm 1 presents the details of the player selection procedure for the ESP algorithm. We initialize a set of candidate players P, a budget constraint B, and the hyperparameters such as mutation probability p_m, crossover probability p_c, and polynomial mutation distribution index η_m. After sorting players based on their salaries, the initial population of a given size is randomly generated by integer coding (Line 1 - Line 7). The first generation of offspring population is obtained by basic operations of crossover and mutation of genetic algorithm (Line 8 - Line 11). Starting from the second generation, the parent population and the offspring population are merged, followed by calculating the CV values and performing the fast non-dominated sorting process with constraints. At the same time, we compute the crowding degree of the individuals in each Pareto front. Note that among the two solutions with different Pareto fronts, we prefer the solution with a better dominance ranking. Otherwise, if the two solutions belong to the same front, we prefer the solution in the relatively less crowded region. According to the crowding degree of individuals, the appropriate individuals are selected to form a new parent population (Line 12 - Line 17). The algorithm loops until the conditions for the end of the program are met.

V. DATA ANALYSIS AND EXPERIMENTS

We implement the algorithms in Python 3.8[5] and conduct all the numerical computations on a Windows PC with a 4-core Intel i5-1135g7 2.40GHz CPU and 16GB memory. All the experimental data is collected from the website https://sofifa.com/ and all the games are simulated in a quick game of PES2021.

A. DATA ANALYSIS

In this section, we analyze the experimental data and present some facts related to our proposed multi-objective function.

[5]Part of the code and dataset are available from: https://github.com/haoyu-zhao/Multi-Objective-Optimization-for-Football-Team-Member-Selection

TABLE 2. An example of football players' athletic abilities.

Ability	L.Messi	Cristiano.Ronaldo
Overall	94	93
Shooting	92	93
...	...	...
Passing	92	82
Dribbling	96	89
Physic	66	78

TABLE 3. An example of football players' personal attributes.

ID	Name	Age	Club	Nationality
1	L. Messi	32	FC Barcelona	Argentina
2	Cristiano	34	Juventus	Portugal
3	Neymar Jr	27	Paris Saint-German	Brazil

We first perform data preprocessing by filtering out some irrelevant attributes and sort the data (in descending order) according to players' salaries. Table 2 and Table 3 list some players' basic properties after data preprocessing. We then elaborate on the three phenomena discovered from the experimental data, which consist of our assumptions.

Algorithm 1 Finding a Best Team Based on ESP Algorithm

Input: *crossover probability*(p_c), *mutation probability*(p_m), *polynomial mutaion parameter*(η_m), *player dataset*(P), *player number*(N), *budget*(B).

Output: *optimal solution set*$(\hat{P})$.

1: $pop = \emptyset$.
2: **// Individual coding and population initialization**
3: **for** $i = 1$ **to** *PopSize* **do**
4: *RandomSequence* = randomly choose the index of N players from P.
5: *individual* = RealNumberCoding(*RandomSequence*, *budget*).
6: *pop*.add(*individual*).
7: **end for**
8: **for** $i = 1$ **to** *Max_Generation* **do**
9: *newpop* = CrossOver(*pop*, p_c).
10: *newpop* = Mutation(*newpop*, p_m, η_m).
11: *newpop* = *newpop* + *pop*.
12: **// Calculate constraint violation for each individual**
13: *CV* = ConstraintViolation(*newpop*, *budget*).
14: *newpop* = FastNondominantSort(*newpop*, *CV*).
15: *crowding* = CrowdingCompare(*newpop*).
16: *offspring* = Selection(*newpop*, *crowding*).
17: *pop* = *offspring*.
18: **end for**
19: **return** $\hat{P}$.

1) WAGES ARE NOT DIRECTLY PROPORTIONAL TO PLAYERS' ABILITIES

We first analyze the relationship between the player's ability and wages. Taking the player's overall rating as the X-axis, the corresponding weekly salary as the Y-axis, we plot the

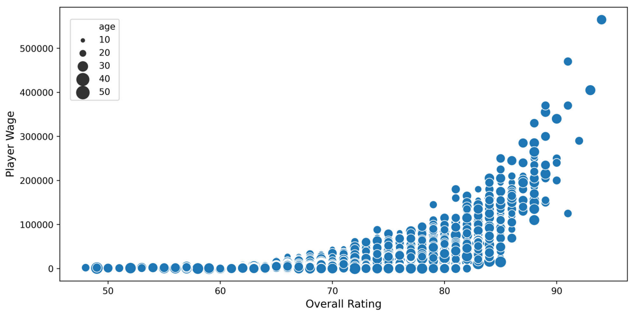

FIGURE 4. Players' wage in the different overall ratings.

relationship in Fig. 4, each dot represents a football player. We can observe that under the same overall ratings, football players have different salaries. This finding is consistent with that we cannot simply measure a player's contribution to a team only based on his salary.

2) POTENTIAL PLAYS AN IMPORTANT ROLE IN FUTURE PERFORMANCE

As described in Section III-C, we consider players' potential value as it plays an important role in team composition. Fig. 5 shows the changing trend of the average value for potential capability and overall evaluation of all players with the increase of age in different football leagues. We observe that the overall evaluation and potential value of young players are quite different initially, while with the growth of age, the potential of future players will be basically consistent with the overall evaluation of players. It means that the potential value of young players can reflect their future performance. The higher potential value may result in a higher overall evaluation in the future. Therefore, it is necessary to consider the player's potential value for football player selection.

3) THERE IS NO PERFECT PLAYER

From the processed data, we observe that there is no perfect football player. We choose three representative attributes from 20 iconic players, including players' overall evaluation, potential value and salary as shown in Fig. 6. Results show that no player is better than other players in all three attributes. We conclude that it is impractical to simply select the player who reaches the best performance in all aspects. It needs a trade-off among the three indicators in Section III, including the player's overall evaluation, the offensive and defensive ability, and the potential value.

B. EXPERIMENT RESULTS

To verify the strength of the team generated by the proposed method, we use our ESP algorithm to solve the optimization problem under two different situations: team composition with or without budget constraints. Furthermore, we also use the t-test to demonstrate the effectiveness of our algorithms. We manually set the bounds of parameters, and then adopt grid search technique to find the optimal parameters based on the simulation time and performance. Hence, the parameters

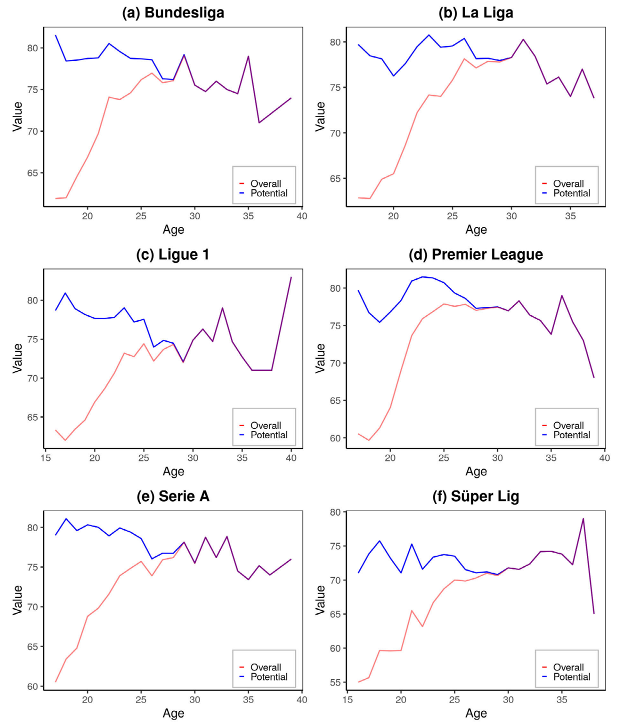

FIGURE 5. The relationship between age and potential value of players in different leagues.

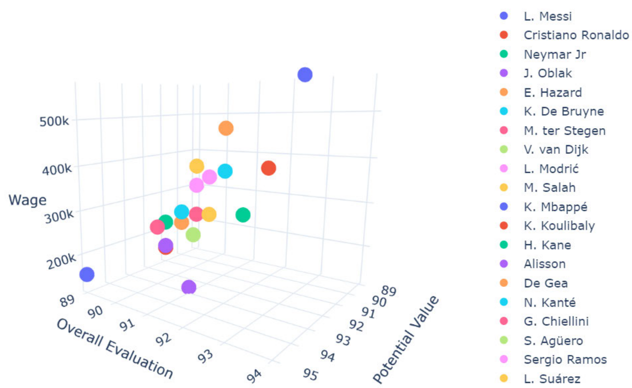

FIGURE 6. The overall evaluation, potential value and salary of 20 iconic players.

of the ESP algorithm are set as follows: $p_c = 0.5$, $p_m = 0.1$, $\eta_m = 30$, $PopSize = 400$, and $Max\_Generation = 300$. The mutation mode of the chromosome is polynomial mutation [35].

We first visualize the results of the ESP algorithm under different budget constraints. Fig. 7 shows all individuals in the last generation population without budget constraints. Similarly, we depict all solutions under a certain budget in Fig. 8. The horizontal axis and vertical axis represent the team's average offensive ability and defensive ability respectively, and the Pareto optimal solutions are marked in red dots. We can observe from Fig. 7 and Fig. 8 that the Pareto optimal solution set achieves better attacking ratings and defensive ratings than other solutions.

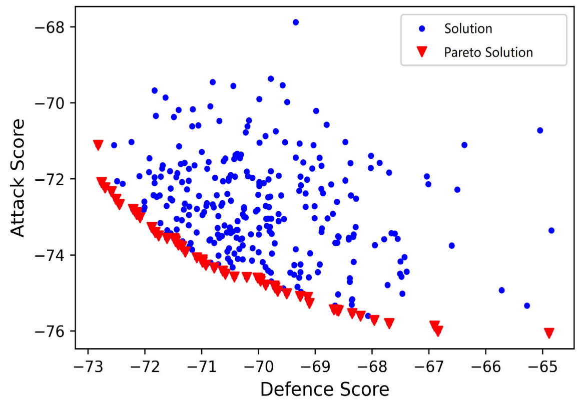

FIGURE 7. Pareto solutions for ESP algorithm without budget constraints.

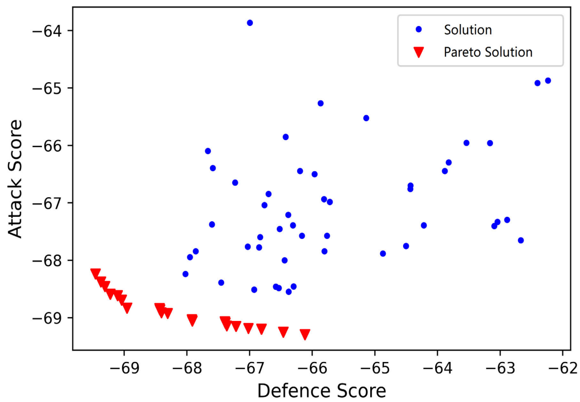

FIGURE 8. Pareto solutions for ESP algorithm with budget constraints.

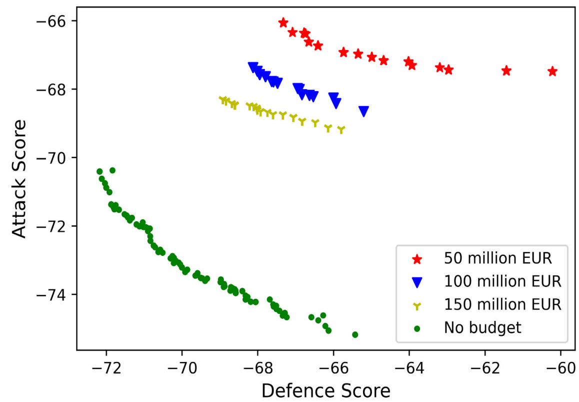

FIGURE 9. The influence of budgets on Pareto solutions.

TABLE 4. Comparison of players' average athletic abilities between the ESP Dream Team and Random Team without budget constraints.

Team's Average Athletic Ability	ESP Dream Team	Random Team
Overall Evaluation	90.6	88.5
Attack Rating	82.6	81.1
Defence Rating	75.1	70.2
GoalKeeping	87.2	82.8
Cost(million €)	770	725

TABLE 5. P-Value (without budget constraints).

Attribute	P-value
Overall Evaluation	0
Attack Rating	6.06×10^{-279}
Defence Rating	4.83×10^{-237}
GoalKeeping	1.19×10^{-159}

Besides, we analyze the Pareto fronts under different budget constraints, as shown in Fig. 9. The green dot set is the Pareto solutions without budget constraints. In Fig. 9, we see that with the increase of the budget, the Pareto front shifts to the lower-left corner, that is, the higher the budget, the stronger the abilities of attack and defense of the team, which is consistent with our assumptions.

As can be seen in Fig. 9, there are many candidate solutions, which form a Pareto front under the same budget. By descending sorting the crowding degree of the solutions in Pareto fronts, we obtain the optimal solution (i.e., the best team). Unless otherwise indicated, we use ESP Dream Team to represent the best team in our simulation experiments.

1) BUDGET UNCONSTRAINED CASE

In this section, we analyze the selection results of the ESP algorithm without budget constraints. We set a large number, which equals 770 million euros to simulate a sufficient budget. Table 4 provides a comparison of players' average athletic abilities between the ESP Dream Team and a random team under a similar total budget level. The players' average athletic abilities include the average of the overall evaluation, attack rating and defense rating, as well as the goalkeeper's goalkeeping ability. In Table 4, we see that the team selected by the ESP algorithm has certain numerical advantages over other teams without budget constraints.

In the t-test settings, given a team attribute (i.e. overall evaluation, attacking rating, defence rating, or goalkeeping), we assume that the team generated from the ESP algorithm and the random team share the same average value. We first take out 200 teams selected by the ESP algorithm, as well as 200 random teams to simulate the distribution of team attribute values with large samples. For each type of teams, we then draw a histogram by calculating the frequency of attribute scores in Fig. 10, and the corresponding P-values are shown in Table 5. Based on the P-value of all attributes, we can reject the original hypothesis with confidence that the average values of any team attribute of both the ESP team and random team are the same, which in turn demonstrates the effectiveness of our algorithm.

2) BUDGET CONSTRAINED CASE

We compare the numerical performance of our team with a randomly selected team under the constraints of the budget in this section. We set the budget at 150 million euros, which is a representative budget of a football team. The comparison results are shown in Table 6. It can be seen that all the numerical results of our proposed method are better than

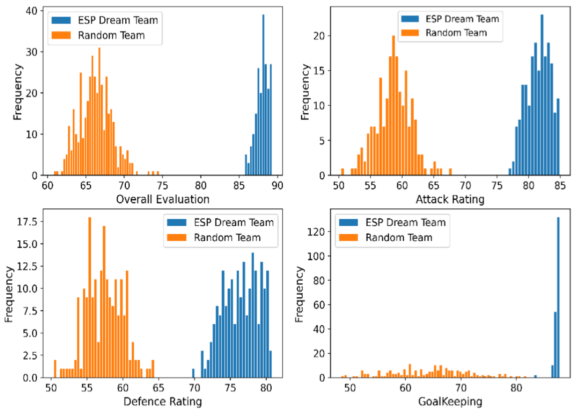

FIGURE 10. Histogram of the distribution of four attributes without budget constraints.

TABLE 6. Comparison of players' average athletic abilities between the ESP Dream Team and Random Team with budget constraints.

Team's Average Athletic Ability	ESP Dream Team	Random Team
Overall Evaluation	81.1	75.5
Attack Rating	77.7	71.8
Defence Rating	78.3	64.1
GoalKeeping	80.0	70.4
Cost(million €)	149	151

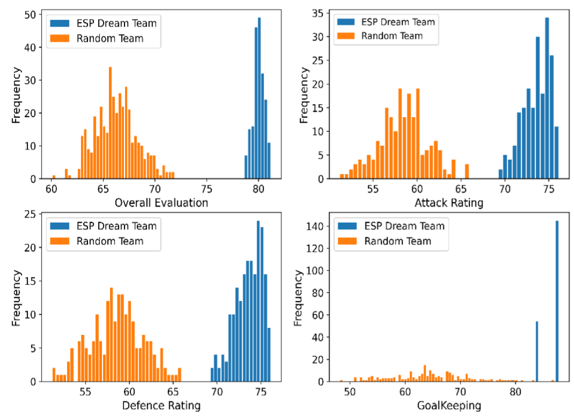

FIGURE 11. Histogram of the distribution of four attributes with budget constraints.

that of the random values. From Table 6, it is clear that the ESP algorithm delivers the best performance in all aspects while using fewer salaries. Similar to the t-test settings in Section V-B1, we show the distributions of all attributes' average values and P-values based on the budget constrained case in Fig. 11 and Table 7 respectively, and the corresponding results also demonstrate the effectiveness of our proposed algorithm.

3) POTENTIAL IMPACT

It is hard to verify the influence of the potential attribute for the football player selection in reality because we can only observe the current performance of players. Therefore, we provide the numerical result of the potential value for a football team. Table 8 shows the optimal solution selected by the ESP algorithm when the budget is 100 million euros. It can be seen that with a similar budget, the ESP algorithm considering the players' potentials can select a team with excellent potential value while keeping the four better mentioned indicators. To better understand the proposed method, Fig. 12 gives a preview of two team's properties, where each dimension shows a kind of average ability. From Fig. 12, we can also see that the team selected by the ESP algorithm is better than the team generated from the random algorithm in all aspects. Likewise, we also show the distributions of all attributes' average values and P-values when considering the potential effect. The corresponding results (see Fig. 13 and Table 9) demonstrate the effectiveness and rationality of the proposed factors in our modeling.

TABLE 7. P-Value (with budget constraints).

Attribute	P-value
Overall Evaluation	0
Attack Rating	2.94×10^{-83}
Defence Rating	1.10×10^{-93}
GoalKeeping	6.12×10^{-117}

TABLE 8. Comparison of players' average athletic abilities between the ESP Dream Team and Random Team with budget constraints considering player potential value.

Team's Average Athletic Ability	ESP Dream Team	Random Team
Overall Evaluation	79.6	71.3
Attack Rating	68.3	62.4
Defence Rating	69.5	63.2
GoalKeeping	79.8	56.4
Cost(million €)	97.0	98.4
Potential Value	81.2	75.3

TABLE 9. P-Value (with potential considerations).

Attribute	P-value
Overall Evaluation	3.56×10^{-144}
Attack Rating	2.02×10^{-109}
Defence Rating	5.60×10^{-113}
GoalKeeping	1.52×10^{-88}
Potential Value	1.27×10^{-163}

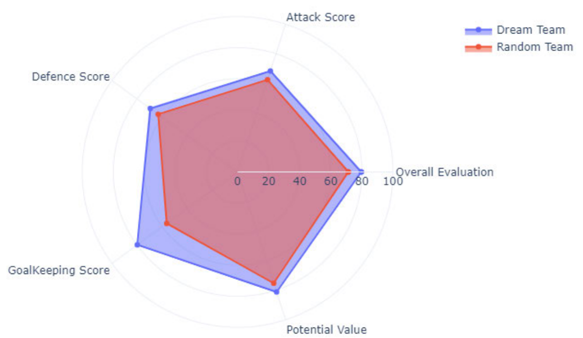

FIGURE 12. Results of players' average athletic abilities of the ESP Dream Team and Random Team.

TABLE 10. Game simulation results of the ESP Dream Team v.s. Random Teams.

Battle	Game Result										Win	Draw	Lose	Tps	Goal Difference
ESP Dream Team	2:0	0:0	4:0	2:0	1:0	3:0	2:0	3:0	3:1	4:0	29	1	0	87	73
vs.	1:0	2:0	1:0	3:0	1:0	4:1	3:0	2:0	4:0	3:0	:	:	:	:	:
RandomTeam 1	4:1	4:0	4:0	3:0	2:0	1:0	2:0	4:0	3:0	1:0	0	1	29	-29	-73
ESP Dream Team	2:0	3:0	2:0	0:0	2:0	3:0	2:0	4:0	3:0	3:0	29	1	0	87	72
vs.	2:0	3:0	3:0	3:0	1:0	3:0	4:0	4:0	2:0	2:0	:	:	:	:	:
RandomTeam 2	4:0	3:0	1:0	2:0	1:0	3:0	3:0	1:0	2:0	1:0	0	1	29	-29	-72

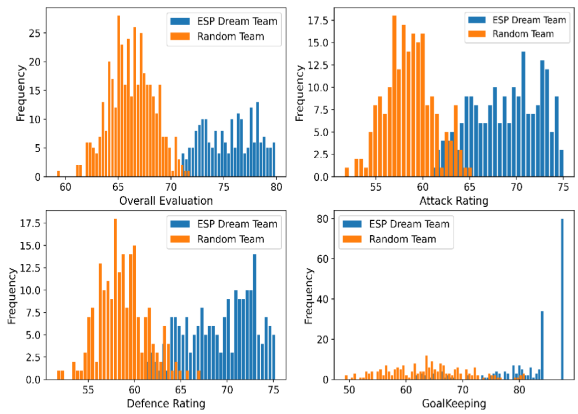

FIGURE 13. Histogram of the distribution of four attributes without budget constraints considering potential considerations.

TABLE 11. Game simulation results of the ESP Dream Team v.s. Ten Representative Real Teams from different football leagues.

Real Team	Game Result					Goal Difference
PSG	3:0	2:1	1:1	3:0	3:1	9
FC Barcelona	3:0	2:0	1:0	1:1	3:0	9
Real Madrid CF	2:0	0:1	3:0	1:0	1:0	6
FC Bayern Munich	1:0	1:0	1:0	0:0	2:0	5
Manchester City FC	1:0	0:0	2:0	0:1	0:0	2
Liverpool FC	1:0	6:0	4:1	1:1	1:0	11
S.S. Lazio	2:0	2:0	1:0	2:1	1:0	7
Olympique de Marseille	2:0	1:0	2:1	2:1	3:0	8
Napoli	0:1	1:0	2:0	2:0	2:0	6
Arsenal	3:0	1:0	0:1	1:0	1:0	5

C. GAME SIMULATION RESULTS

The numerical results cannot reflect the match level of a football team. In this section, we show the competition results of football simulation games using the PES2021 platform to verify the actual effectiveness of our algorithm. Two metrics are used for evaluating the results, one is *Goal Difference*, which refers to the net wins, the other is *Total Score* defined as follows:

let $g = \{g_1, g_2, \cdots, g_M\}$ be a competition result set, M is the number of matches, we use Tps to represent the total score of the team in Eq. (5):

$$Tps = \sum_{i=1}^{M} \omega_{g_i} \tag{5}$$

where ω_{g_i} is the score of a match g_i and its definition is in Eq. (6):

$$\omega_{g_i} = \begin{cases} 3 & \text{Win} \\ 0 & \text{Draw} \\ -1 & \text{Lose} \end{cases} \tag{6}$$

Followed by the procedure in Section V-B, we verify the performance of the proposed method under different budget constraints.

1) BUDGET UNCONSTRAINED CASE

We first compose the ESP Dream Team based on unconstrained budgets for the PES2021 game simulation. To compare the algorithm performance, we randomly select teams without any constraint and simulate the battle between the two teams. The match results are listed in Table 10, including specific results of every match, the total score and the Goal Difference. As can be seen from Table 10, we win 29 out of 30 games, which indicates the ESP Dream Team is dominant in most of the matches, which is exactly what we expected.

Besides, we make our ESP Dream Team against ten teams that have the leading record in their respective football leagues, such as Real Madrid CF[6] and Manchester City FC.[7] Results are shown in Table 11, we can see that in the face of different teams, the ESP Dream Team still achieves better performance. Furthermore, we choose two representative teams (i.e. FC Barcelona[8] and Paris Saint German F.C.[9]) and then battle with the ESP Dream Team, respectively. The corresponding results are displayed in Table 12. Similarly, it can be seen that the ESP Dream Team wins most games with vastly superior forces, which dominates most of the competitions.

2) BUDGET CONSTRAINED CASE

Similar to the unconstrained numerical experiments, we test the effectiveness of our algorithm under a constrained case. We compose the ESP Dream Team under the budget of 150 million euros and conduct thirty soccer matches with two

[6] https://www.realmadrid.com/
[7] https://www.mancity.com/
[8] https://www.fcbarcelona.com/
[9] https://www.psg.fr/

TABLE 12. Game simulation results of the ESP Dream Team v.s. Real Teams.

Battle	Game Result										Win	Draw	Lose	Tps	Goal Difference
ESP Dream Team	1:0	2:0	1:0	2:0	1:0	2:0	2:0	2:0	1:1	0:0	26	4	0	78	40
vs.	0:0	2:0	2:0	2:1	1:0	1:0	2:0	1:0	2:1	1:0	:	:	:	:	:
FC Barcelona	3:0	2:0	1:0	1:1	1:0	3:0	1:0	2:0	1:0	1:0	0	4	26	-26	-40
ESP Dream Team	2:0	1:0	2:1	2:0	0:0	3:0	4:1	2:0	1:1	1:0	22	8	0	66	42
vs.	1:0	1:1	2:1	1:1	1:0	2:0	4:0	1:0	1:0	0:0	:	:	:	:	:
Paris Saint-Germain F.C	4:0	0:0	3:0	3:0	2:1	0:0	3:0	2:1	2:1	1:1	0	8	22	-22	-42

TABLE 13. Game simulation results of the ESP Dream Team (with budget constraints) v.s. Random Teams.

Battle	Game Result										Win	Draw	Lose	Tps	Goal Difference	Budget Comparison(million €)
ESP Dream Team	1:0	0:0	1:0	3:0	1:0	2:0	2:1	3:0	2:1	3:0	27	3	0	81	57	149
vs.	2:0	1:0	2:1	0:0	4:0	3:0	2:0	5:0	4:1	1:0	:	:	:	:	:	:
RandomTeam 1	1:0	7:0	1:0	2:0	1:0	0:0	2:0	1:0	3:1	2:0	0	3	27	-27	-57	151
ESP Dream Team	1:0	2:0	2:0	0:0	1:0	1:0	2:0	2:0	2:1	1:0	25	5	0	75	42	149
vs.	1:0	1:0	0:0	4:0	2:0	3:0	2:1	1:0	0:0	2:0	:	:	:	:	:	:
RandomTeam 2	2:1	0:0	1:0	1:0	2:0	0:0	2:0	2:0	2:1	4:0	0	5	25	-25	-42	152

TABLE 14. Budget level.

Budget Level	Corresponding Budget Range
Level I	$[100, 150)$
Level II	$[150, 200)$
Level III	$[200, 250)$
Level IV	$[250, 300)$
Level V	$[300, 350)$
Level VI	$[350, 400)$
Level VII	$[450, 500]$

random teams with similar budget constraints respectively, and the corresponding match results are shown in Table 13. Despite lower goal differences compared to that in Table 10, the ESP Dream Team still outperforms the two random teams with a similar total budget.

Following the simulation competition with random teams, we also fight the ESP Dream Team with real teams under different budget levels (see Table 14). We first select several budget levels, for each budget level, we generate the ESP Dream Team by the proposed method and pick up a representative real team under the similar budget level. We then simulate 30 battles between two teams as shown in Table 15. Notice that the simulation results cover different budget levels, including teams with lower total salaries, such as Everton[10] and Olympique Lyonnais,[11] as well as teams with moderate and higher budgets, such as Juventus[12] and PSG. Specifically, there are two observations from the table. First, all four ESP Dream Teams win the most matches against real teams under the same or even higher budget level, which demonstrates that the ESP algorithm generates promising performance. Second, no matter how much we limit our budget, there is almost no change to the numerical value of Tps achieved by the ESP Dream team, which indicates the stability and reliability of the proposed algorithm.

[10]https://www.evertonfc.com/

[11]https://www.olweb.fr/

[12]https://www.juventus.com/

VI. METHOD COMPARISON

In this section, we compare our model with other approaches from two perspectives. One is the different ways of team composition methods, the other is the different methods for solving the multi-objective optimization problem.

A. COMPARISON OF TEAM COMPOSITION METHODS

In this part, we present the comparison results between our team composition strategy and the one proposed in [11]. In [11], the authors converted the team composition into a submodular optimization problem and proposed an algorithm called CEFG (Cost-Effective Forward selection Greedy) to solve it. We again use the PES game platform mentioned in Section V to compare our ESP with the CEFG algorithm. We first record the best team generated by the ESP and CEFG respectively, then simulate 30 game battles between these two selected teams. The simulation results are summarized in Table 16. It can be seen from this table that among all 30 matches, the team selected by our ESP algorithm loses only three games and achieves good performance in goal difference, which demonstrates the effectiveness of our method. A possible explanation for this observation might be that the team composition approach proposed in [11] ignores the players' positions and the future ability of a team, while both of which are incorporated in our method.

B. COMPARISON OF MULTI-OBJECTIVE OPTIMIZATION METHODS

In addition to NSGA-II, there are several algorithms on solving multi-objective optimization problems. Here we select another classical multi-objective optimization evolutionary algorithm (i.e., MOEA/D) [18] for comparison. MOEA/D transforms a multi-objective optimization problem

TABLE 15. Game simulation results of the ESP Dream Team (with budget constraints) v.s. Real Teams.

Battle	Game Result										Win	Draw	Lose	Tps	Goal Difference	Budget Comparison(million €)	Budget Level
ESP Dream Team 1	0:1	3:0	3:0	3:0	3:0	2:0	1:0	1:1	4:1	2:0	25	3	2	73	55	149	Level I
vs.	3:0	3:1	3:1	2:1	1:1	2:0	3:0	1:0	3:0	0:1	:	:	:	:	:	:	:
Everton	3:0	2:0	2:0	3:0	2:0	3:0	3:1	1:0	2:0	0:0	2	3	25	-19	-55	261.6	Level IV
ESP Dream Team 2	1:0	1:1	1:0	1:0	0:0	1:0	1:0	1:1	2:0	1:0	21	8	1	62	26	197.6	Level II
vs.	0:0	2:1	1:2	2:2	1:0	1:0	2:0	1:0	3:0	2:1	:	:	:	:	:	:	:
Olympique Lyonnais	2:1	2:1	2:0	2:1	1:1	2:0	1:0	1:0	1:1	0:0	1	8	21	-18	-26	207.5	Level III
ESP Dream Team 3	0:0	2:0	1:0	0:0	2:0	1:0	1:0	2:0	2:0	2:1	22	8	0	66	33	297.7	Level IV
vs.	2:1	1:1	2:0	3:0	0:0	1:0	2:0	1:1	1:0	2:0	:	:	:	:	:	:	:
Juventus	1:1	1:0	1:0	1:0	0:0	2:0	2:1	1:0	0:0	2:0	0	8	22	-22	-33	346.5	Level V
ESP Dream Team 4	0:0	2:1	3:0	3:0	1:0	3:0	2:0	2:0	3:1	2:1	23	7	0	69	48	397.7	Level VI
vs.	0:0	2:1	3:0	2:0	3:0	2:1	1:1	2:0	3:0	1:1	:	:	:	:	:	:	:
PSG	1:0	1:1	2:0	1:1	0:0	2:0	3:0	3:0	3:1	2:0	0	7	23	-23	-48	420	Level VII

TABLE 16. Game simulation results of the ESP Dream Team v.s. CEFG Dream Team.

Battle	Game Result										Win	Draw	Lose	Tps	Goal Difference
ESP Dream Team	3:1	1:0	0:0	2:0	0:1	0:0	0:1	2:0	1:0	1:0	18	9	3	51	26
vs.	2:0	2:0	3:0	2:0	0:0	1:0	0:0	0:0	1:0	0:0	:	:	:	:	:
CEFG Dream Team	3:1	2:0	1:0	0:0	0:1	1:0	0:0	2:0	2:1	1:1	3	9	18	-9	-26

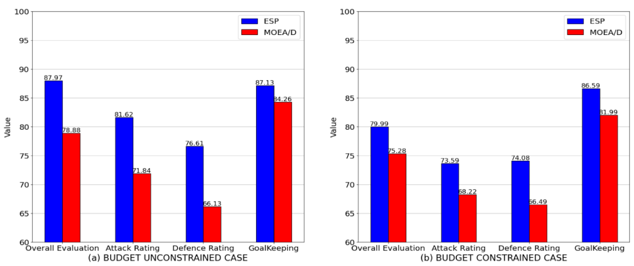

FIGURE 14. Performance comparison between the ESP and modified MOEA/D algorithm.

into a number of scalar quantum sub-problems and each sub-problem is composed of a uniformly distributed weight vector, which helps to generate the single objective function. In order to apply it for our team composition problem, we modify the MOEA/D algorithm, which mainly includes:

- Changing the coding method: we set the solution as a vector of players whose length is equal to the number of team members;
- Adding constraints: for each iteration, the solution generated from MOEA/D method needs to be repaired until it satisfies the budget constraint;
- Target normalization: when using the MOEA/D, it is necessary to normalize the values of attributes mentioned in Section III.

We use the modified MOEA/D algorithm to compare with the ESP method under the same parameter settings. The numerical results are shown in Fig. 14. From the results, we can see that the team generated by the ESP algorithm achieves the leading performance. These advantages may be partly due to the particularity of the coding method, coupled with the ESP algorithm whose framework based on Pareto dominance can achieve better results. In addition, if we increase the number of iterations, the MOEA/D algorithm will run slower than the ESP algorithm.

VII. CONCLUSION AND FUTURE WORK

In this paper, we give three evaluation indicators for football team composition, including overall evaluation, offensive and defensive abilities, and players' potential value. We formulate the team composition issue as a multi-objective optimization problem and propose a variant of the genetic algorithm named ESP, which can automatically output and recommend a football team with a high winning rate by quantifying the players' abilities under a certain budget constraint. We also discuss the effectiveness of our approach and the results demonstrate the strength of teams generated via the proposed approach.

Despite these satisfying results, there is still room for improvement. For example, when recommending football team members, the existing ESP algorithm has no subjective and emotional input, as well as the lack of consideration of the decision makers' personal preferences. For instance, a football team coach who values the team's defense may choose players with higher defensive ability. To solve this problem, we can develop a customized GUI (Graphical User Interface) based user-friendly software for users to personalize all attributes of the team composition problem. Besides, another work is that the program developed here can be extended to other similar sports fields, which we will postpone as a recent study.

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