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Research Article

Analysis and Modeling of Football Team's Collaboration Mode and Performance Evaluation Using Network Science and BP Neural Network

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With the continuous development of society, the cooperation of different dimensions is urgently needed. Analysis and modeling of team cooperation model and performance evaluation are especially important for competitive sport. In this paper, a football team's attacking mode and the team performance were assessed using network science methodologies. The match process was analyzed by using the data of Team A (given in the form of attachment due to excessive file size) and the method of complex network science. Each player was regarded as a node in the network, and the interaction among players was considered as the connection to the network. This method directly reflected the favorable formation of the team and the interaction frequency among members. Then, a team performance evaluation model was established using the backpropagation neural network (BPNN) and the uncrossed analytic hierarchy process (U-AHP) method based on the factors including the number of passes and successful pass rate. The team performance was comprehensively rated from two levels: member and team level. Analysis from established models indicated that Team A had a higher probability of winning when using the "4-4-2" offensive strategy and performance evaluation analysis indicated that more passes and higher pass success rates were more beneficial to win the game. Following the model developed in this study, some suggestions were given from the perspectives of team strategy, attack mode, cooperation, and incentive mode.

1. Introduction

Football is known as the "world's first game" and the most influential sport in the world [1]. The standard 11-player football match consists of 10 players and 1 goalkeeper from each team, 22 players in total who fight, defend, and attack on the rectangular grass field [2]. In the game, players from both sides try to shoot the football into the goal of the other side. The more goals your team scores, the better your chances of victory [3]. When the game is done, the team scoring more goals wins [4]. Tie results are generally allowed, except in certain situations, such as knockout rounds. If the scores are the same within the specified time of the game, it shall be determined by the rules of the game, and the scores can be higher in the form of drawing lots, extra time replay, or penalty kick (12 yards) as well [5].

Network science is widely used in the classic problems of the social system [6], such as the stimulation of cooperation among individuals, epidemic infection, or the spread of information on social networks [7]. The football team's playing style and personal contribution can be revealed through indicators from network science [8].

The current research on the cooperative system mainly focuses on the cooperative process and the cooperative results [9–11]. The research of the collaborative process mainly lies in the behavioral characteristics of both partners, which can be explicit or implicit. For instance, Reid et al. [12] proposed a semistructured interview method to study the collaborative process between nurses and patients and finally found that the collaborative process between patients and nurses was conducive to the formulation of care planning. Research on the collaborative results mainly focuses on the team performance evaluation. In the process of team collaboration, the influence of the factors and the degree of the collaborative results are analyzed. For example, Yang et al [13]. proposed a moderated mediation model to analyze the relationship among team reflexivity, team diversity, and team performance and found that team diversity can enhance the mediation relationship between team reflexivity and team reflexivity. This paper mainly uses the CNS method to establish and analyze the football team's cooperation network and uses the BPNN method to evaluate the team's performance.

The CNS method can analyze the whole process of the football match and the collaborative network established by it is both flexible and dynamic, which can not only reflect the overall situation of the team but also track the dynamics of each player during the game. This is the case in the study by Buldu et al [5, 14]. This paper mainly uses the CNS method to analyze the cooperation problems in football teams and through the use of a large number of match data to build a matching network and then to reveal the mechanism of team cooperation, focusing on the team's attack and defense strategy. In the process of constructing the passing network, the CNS method used by Buldu et al. was adopted [3, 15]. However, when determining the weight among nodes, the entropy method was not adopted, but the corresponding improvements were made according to the actual game data.

One of the classic methods of performance evaluation use the key performance indicator (KPI) index method, but this method is gradually replaced by BPNN due to its limitation in weight assignment. For instance, Dony et al [16]. proposed a hybrid principal component neural network method to evaluate the compression performance of digital chest radiographs. The evaluation process is fully quantifiable, and the evaluation results are highly reliable. In this paper, based on the performance evaluation model of nonprofit hospitals based on BPNN proposed by Li and Yu [17], the irrationality of its weighting is improved, and the model is applied to team performance evaluation. As the team's performance evaluation is relatively complex, it has a great impact on the accuracy and convergence speed of the network [18–20]. The solution proposed in this paper is to enhance the adaptability of the evaluation network by using a large amount of data, thus greatly improving the accuracy of the interpretation of the network.

2. Methods

2.1. Complex Network Science. Complex network science (CNS) is a development of the graph theory approach, in which CNS can analyze more complex and dynamic systems. The advantages of using the CNS analysis system are shown as follows [21–23].

For a large system, the behavior of the system cannot be explained from an individual perspective. The point of network science is that by representing individuals with nodes, directed or undirected segments among nodes represent the connection between two individuals. When enough points and lines are used to describe the system, a network is formed and usually represented by an adjacency matrix so that a system is rationally characterized [24]. Then the network method is used to analyze the distribution of point and line and the interaction between points. Finally, the results are mapped to the system to describe the relationship among system members.

The aggregation state of system members can be explained and analyzed by using the aggregation coefficient of the network. For the network, the weight and orientation among nodes determine the degree of point aggregation [25]. The clustering coefficient expresses the probability of a connection between two indirectly related nodes. There will be another state between the members of the system. At a certain point in the future, the relationship among the members of the system will change with the continuous evolution of the system [26–28]. At this point, the CNS method can be used to analyze the evolution form of the system and the connection form of the members in the future [29].

System cooperation and division of labor can be characterized by the degree of nodes in the network. In reality, the members of a system have different roles to play while for a network the degree of nodes reflects the connection status of it whether it is tight or loose. By mapping the analysis results to the system, the cooperative division of labor among members can be analyzed [30].

Going back to the system to be analyzed, it is necessary to consider the errors generated by replacing the system analysis with the CNS method [31]. Since the distribution of system members is extremely random, and the change of nodes in the network is limited within a certain probability range, the difference itself will bring errors [32].

2.2. BPNN. BPNN is an artificial neural network whose analytical process is similar to the decision-making process of neurons in the human brain [33]. BPNN is a kind of supervised self-learning whose learning behavior is essentially receiving potential guidance. Using BPNN to analyze team performance evaluation has theoretical advantages [34–36].

First of all, team performance evaluation is a continuous function of many complex factors, and the change of each factor affects the overall performance of the team [37–39]. These factors can be at the member level, for example, a member's behavior will have a great impact on the team's score and then affect the team's performance, such as passing, shooting, and foul [40]; it can also be at the team level [41], for example, when each member performs consistently, the team's flexibility and strategy changes can also

affect the team [42–44]. The theoretical study shows that a three-layer BPNN structure can approximate any continuous function. This lays a foundation for analyzing performance evaluation with BPNN [45].

Secondly, to determine the input of BPNN is the foundation of network construction and we need to analyze what kind of data will affect the team performance from two levels according to the specific team [45–47]. Determining the number of hidden layers is the key to ensure the accuracy of BPNN. In this paper, the theoretical formula and trial-and-error method are combined, and the analysis results are satisfactory. To determine the network output is a necessary step of BPNN, and to determine a reasonable network output can make the results intuitive.

Finally, it is a better method to judge and improve the network by using a regression level and error training state. The regression level reflects the best approximation level of BPNN for performance evaluation function. The error training state reflects the variation of error in network training.

3. Implementation Methods

3.1. Data Processing and Assumptions. When analyzing the competition, all the matches of Team A (38 games in total) are analyzed, which makes the relevant data of Team A and its competitors available. The number of successful passes, shots, x-coordinate relative to the network center of mass, y-coordinate relative to the network center of mass, and the number of passes each player made to the other ten teammates are counted. The above statistical data to calculate the position, personal strength, playing style, and the possibility of passing to the other ten teammates are weighted. Several basic assumptions can make the analysis process simplified. (1) It is assumed that in every game of Team A, there is no condition other than performance. (2) It is assumed there is no correlation between team-level factor set and member level factor set. (3) It is assumed that the change of team coach only affects the internal factors of the team, and there is no other external influence.

When analyzing the team performance, the data used in this model are mainly from the full event.csv, passing event.csv, and matches.csv provided by the Consortium for Mathematics and Its Application (COMAP). After processing, it is stored in a file named data1.mat, which contains two subdatasets named P and T. Each column of dataset P represents 38 matches against Team A, and each row represents 11 event types including foul and pass. Dataset P is mainly used to input the original data of BP neural network training. When using the U-AHP method to analyze the weight, the relevant data in three documents need to be used, which will not be discussed here. The following formula shows the data normalization formula:

$$\lambda_{ij} = \frac{\varepsilon_{ij} - \varepsilon_{j\min}}{\varepsilon_{j\max} - \varepsilon_{j\min}}, \tag{1}$$

$$\begin{aligned} \Delta w &= \frac{\partial E}{\partial W} = -(d_k - y_k) f(x)', \\ \Delta b &= \frac{\partial E}{\partial b_k} = -(d_k - y_k) f(x)'. \end{aligned} \tag{2}$$

3.2. Analysis and Modeling Based on Network Science. Python is used to create a network for passing among players, in which each player is a node, and each passing constitutes a link between players. Using network science, the team is regarded as a complex network, whose nodes (players) interact to overcome the opponent network. Different network indexes are used to extract the characteristics of Team A, including the times of passing, shooting, x-coordinate of relative network center of mass, y-coordinate of relative network center of mass, shortest path length, the maximum eigenvalue of the adjacent matrix, and algebraic connectivity. At the same time, the influence of the opponent's network attribute on Team A's network attribute is considered. A variety of scales, such as micro (individual) to macro (all players interaction), and time, such as short (minute to minute) to long (the whole game and the whole season), are explored. The main steps for establishing a network are as follows.

Speculate the player's position by averaging the x-coordinate of each player's relative network centroid and y-coordinate of relative network centroid, and take them as the node coordinates.

Calculate node radius R. The size of player node R depends on its passing times P and shooting times S:

$$R_{ij} = \frac{p_{ij}^2}{p_{j\max}\left(p_{ij} + s_{ij}\right)} + \frac{s_{ij}^2}{s_{j\max}\left(p_{ij} + s_{ij}\right)}. \tag{3}$$

Determine the link width W. The width of the pass link W between the player and the teammate depends on the number of passes P between the player and the other ten players:

$$w_{ij} = \frac{p_{ij}}{p_{j\max}}. \tag{4}$$

Based on the analysis above, the competition processing at one time is shown in Figure 1 (refer to the appendix for the player number represented by the label).

According to the network diagram above, a lot of information can be extracted.

(1) Team A is good at defense in the game. It is not hard to find that Team A's defenders and avant-garde are relatively backward; accordingly, this team is more defensive than offensive. It can be inferred that the playing style of Team A should follow the trend of "5,4,1". The highlight of the team's defense is that it can not only maintain the width of defense, but also quickly build up enough defense strength in the middle and maintain the situation of "2 vs. 1". Of course, such a team also has a natural disadvantage is weak on the counterattack.

(2) The players of Team A have a clear division of duties, especially in passing. Player a can be said to be the player who loves passing the ball most. In 38 games, player a has passed 1225 times, while player II passed 859 times successfully and player I has only 238 times. However, when processing the data, it is found that the number of times I passes

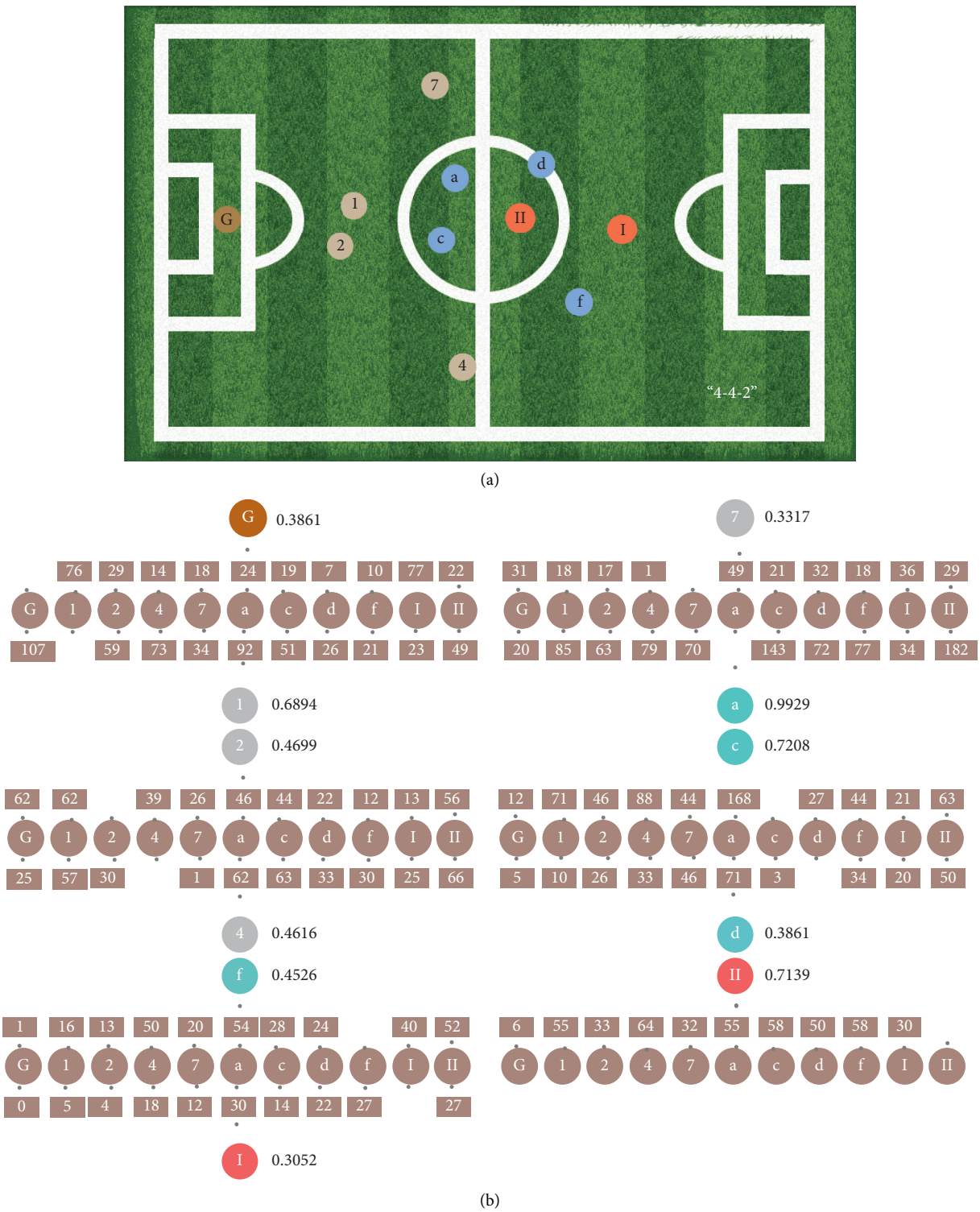

Figure 1: Average passing network. (a) The distribution of the players; (b) number of passes between members (members are denoted by codes and the detailed information is shown in the Appendix).

to striker F2 is half of the number of times that II passes to striker I who is farther away. Almost all of the 38 games are like this and it is reasonable to speculate that the division of duties between them is very different.

(3) There are similar formation characteristics in the failure cases of Team A. Team A's two matches against opponent 9 are shown in Figures 2(a) and 2(b). According to the best pass network, the best formation should be "4-4-2". From the perspective of

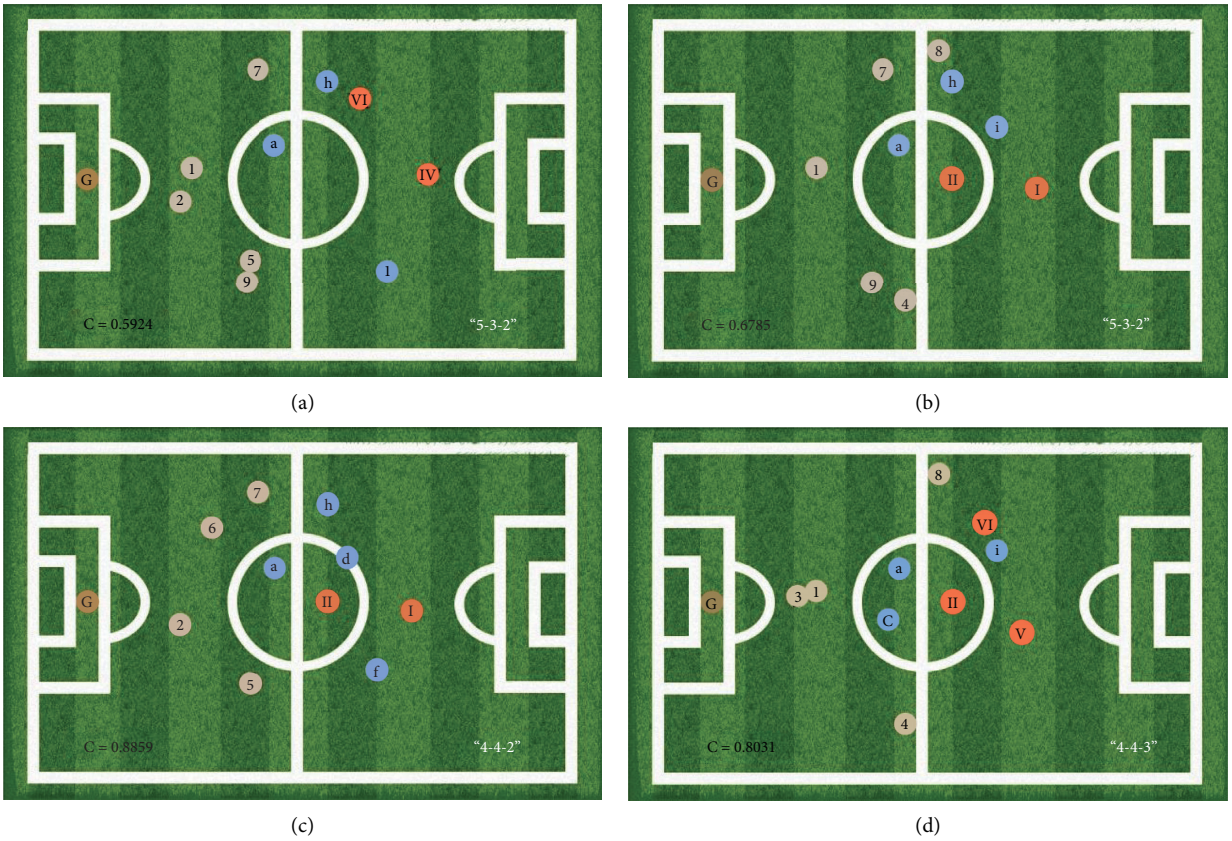

Figure 2: (a) Team A vs. opponent 9 second game; (b) Team A vs. opponent 9 first game; (c) Team A vs. opponent 15 first game; (d) Team A vs. opponent 15 second game.

the lineup, Team A adopts "5-3-2" (defensive lineup) rather than our best team "4-4-2". In the first game, the position of the central defender was crucial, but he did not play a role and the defensive strength of the central road was sacrificed. Besides, the defense width has also been reduced. In the second game, the defenders 1, 9, and 7 are too dispersed although they kept the defensive width. The "4-2-2" formation was regarded as the standard, and the clustering analysis of the adopted formation showed that the clustering coefficients were "0.5924" and "0.6785," respectively. From the perspective of personal strength, only four of the best players predicted are selected in the first game while seven are selected in the second game, but none play their due role due to the lineup. The final game was a 1-5 and 2-5 fiasco, respectively.

(4) There are similar formation characteristics in the successful cases of Team A. Team A's two matches against opponent 15 are shown in Figures 2(c) and 2(d). According to our best pass network, the best team should be "4-4-2". From the perspective of the lineup, Team A adopts "4-4-2" and "4-3-3" lineups. Similarly, the clustering coefficients of the two matches were "0.8859" and "0.8031," respectively. In terms of personal strength, 8 members of the best players predicted are selected. The results were 2-0 and 2-0.

3.3. Analysis and Modeling Based on BPNN. Firstly, the structure of the neural network needs to be determined. Theoretical research shows that the BP neural network with a three-layer structure can approach any differentiable nonlinear functions, but this structure will fall into the local optimal solution. Therefore, this thesis introduces the momentum factor which can avoid entering into local optimum and accelerating convergence. Figure 3 shows a flowchart of performance evaluation using the BP neural network.

It is exceedingly crucial to determine the number of hidden layers of the BP neural network for the calculation stability of the neural network. Although there are many empirical formulas in practice, this method often produces large errors. The method selected in this thesis is the combination of the empirical formula and trial-and-error method, which not only avoids the error of relying on empirical formula, but also reduces blindness. Determining the transfer function of the BP neural network is conducive to accelerating convergence. Since there is no negative

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Input: P_i, T_i, exp_i, ne, ng, nl, nmc
Output: ps_i, ts_i, pre, bhl, psout_i, tsout_i, outsim_i
for i = 1, ···,n_iter do
    Find the best number of hidden layers using equation (5)
    hl = log_2 (inl + oul) + exp
    if exp ≥ 1 and exp ≤ 10 then
        Normalize data using equation (1)
        ps_i = (P_i − min (P_i))/(max (P_i) − min (P_i))
        ts_i = (T_i − min (T_i))/(max (T_i) − min (T_i))
        psout = min max (P_i); tsout = min max (T_i)
        Calculate partial derivatives of network weights and bias using equation (2)
        Δw = (∂E/∂W) = −(d_k − y_k)f(x)′; Δb = (∂E/∂b_k) = −(d_k − y_k)f(x)′
        Initialize and update the network weights and bias
        for j = 1, ···,m_iter do
            for l = 1, ···,l_iter do
                w_jl = w_jl + Δw; b_jl = b_jl + Δb
                h_jl = f(ps_jl); ps_jl = Σ_{j=1}^{sl−1} w_jl h_j(l−1) + b_jl
            end
        end
    else
        Return;
    end
    outsim_i = net (ps_i, ts_i)
end
```

Figure 3: Flowchart of team performance evaluation based on the BP neural network.

number transformation in the data of this problem, log-sig function and tan-sig function are selected as the transfer function.

In order to study the problem stratification, the contribution of the scheme layer to the target layer is obtained through the weight relationship not only between the criterion layer and the target layer but also between the criterion layer and the scheme layer. This method can simplify a complex problem layer by layer, especially suitable for quantitative analysis of qualitative problems. There is a kind of problem that the scheme layer and the criterion layer are independent of each other, but the target layer is consistent, which is the case of the performance evaluation studied in this paper. In the above problems, the uncrossed weight between factors can be solved by using the U-AHP method, that is, the weight of each criterion layer is obtained and then the total weight of the scheme layer to the target layer is obtained by using the weight transfer. Compared with the analytic hierarchy process (AHP), the U-AHP is not different in essence, but slightly different in the calculation of weights. The specific application methods are shown in the modeling process of this thesis, which will not be described in detail here.

In this model, the number of input layers is 9 and the number of output layers is 4. The data of the input layer mainly include nine actions of team members' passing and shooting in 38 games. The data of the output layer includes four indexes: own and opponent's score, game results (measured in terms of 0 and 1, win-1, lose-0), and successful passing times, shown in Table 1.

The number of hidden layers and network parameters are determined, among which the setting of network parameters mainly includes maximum learning times, learning rate, learning target error, and momentum factor. The programming language is shown in Table 2.

The general empirical formula for the number of hidden layers is given by

$$\mathrm{hl} = \log_2 (\mathrm{inl} + \mathrm{oul}) + \mathrm{exp}, \tag{5}$$

where inl and oul are the number of input layers and output layers, exp is the error term, and its value is (1, 10). The number of hidden layers selected in this thesis is 12. After the network parameters are determined, the weight of team members' behaviors can be easily obtained by using the test data. When analyzing team-level factors, the factors including adaptability, flexibility, rhythm control, and the opponent strategy are selected as indicators. The specific contents of each indicator are shown in Table 3.

By using the existing data and entropy weight method, the evaluation network based on team level is constructed.

The U-AHP method is used to build the total performance evaluation index of the team, and the classical

Table 1: Input layer and output layer factors of the BP neural network (the data related to the factors are given as an attachment).

Input layer	Output layer
Free kick Duel	Own score
Foul Goalkeeper leaving line Offside	Opponent score
Others on the ball Pass	Result
Save attempt Shot	Successful passing times

Table 2: Four key parameters and their actual meanings input in the BP neural network program.

Content	Meaning
Net.trainparam.epochs = 1000000	Maximum learning times
Net.trainparam.goal = $1e-5$	Learning target error
Net.trainparam.lr = 0.035	Learning rate
Net.trainparam.MC = 0.3	Momentum factor

Table 3: The content of the team factor.

Adaptability	Flexibility	Rhythm control	Rival strategy
Home	Coach 1	Pass	Other on the ball
Away	Coach 2	Save attempt	
	Coach 3	Shot	

method of calculating the weight of AHP is used to obtain the total weight of members and teams to the goal. It should be noted that because the weight of the member level and team level to the overall goal is relatively large, the method of performance appraisal KPI is introduced to evaluate the weight of the two overall indicators of the overall goal.

4. Results and Discussion

4.1. Character of Team A in Competition. By selecting the specific data of Team A's passing and shooting in the whole season (the number of passes is 14043, and the number of shots is 320), it is concluded that the weight of passing is far greater than that of shooting.

The number of successful passes of each player is statistically analyzed, and the best position of players with a passing success weight of 91.84% (as shown in Figure 4(a)) in the whole season is highlighted (as shown in Figure 4(c)).

Analyzing the players' combination that Team A won the game, such as the first, 6th, 11th, 14th, 15th, 17th, 18th, 25th, 27th, 30th, 31st, 35th, and 36th game count the frequency of each player's appearance, and Figure 4(b) is obtained.

By further analyzing the data, the passing data of each player is obtained and shown in Table 4 and Figure 5.

It can be seen from Figure 5(a) that G is the goalkeeper, II and d play in every game. Player 1–7, I, a, c, and f have high attendance (more than half of the total number of games), which shows that the positions of these players have a great influence on the rhythm control, passing, and shooting. Of course, there are players with similar attacking positions and passing methods, such as 2, f and 3, 4, and 5, 6 and 7. Coaches may employ alternate tactics. From Figures 5(a) and 5(b), based on meeting the requirements of more passing times and higher success rate, the passing energy of a, II, 1, c, 3, 5, G, 4, 2, f, d, 7, and other players is better, which can be given priority in the analysis of structural strategy. It can be seen from Figure 5(b) that I, II, IV, f, and other players shoot the most times, who should be the shooter of the team and to a large extent can determine the choice of the striker in each game.

Finally, the comparison of ten football indexes is listed between Team A and the enemy team in the season (as shown in Figure 6). In the given index, the left column is the average index value of Team A and the right column is the average index value of 19 enemy teams. The indexes in the figure include the number of free kicks, the number of duels, the number of fouls, goalkeeper leaving the line, offside, other on the ball, passes, save attempts, shots, and times of transmission. Also, in Figure 6, the difference between Team A and the other 19 teams is mainly in the number of shooting and passing, which is mainly since Team A is a team with conservative tactics. It can be seen that Team A has a good overall consistency for the ball. The team members of Team A have strong cohesion, so they have a good control of the rhythm of the game.

Figure 6 shows a comparison of the 10 parameters directly related to the topology of the average through the network and gives a detailed description. In the previous figure (Figure 2), the game data are plotted, which are related to the number of triangles created among any three players. The clustering coefficient is an indicator of the local robustness of the network because when a triangle connecting three nodes exists, the link between two nodes is lost, and there is another way to reach another node passing through the other two sides of the triangle. In football, the clustering coefficient measures the triangulation among three players.

In the first question, Team A can be roughly inferred to play conservatively through a passing network. Figure 6 illustrates this problem even more powerfully. An analysis of Team A shows that Team A is more defensive in the game. For example, Team A has more passes and duel times, which are indicators of defensive strategy. Another defense strategy is the number of fouls and not surprisingly Team A has a great number of fouls.

4.2. Team Performance Evaluation of Team A in Competition. Firstly, the method of neural network is used to evaluate the indicators of member level, and the regression level and error training are as follows (Figure 7).

The regression level reflects the interpretation of variables to the results. The closer the value is to 1, the better the interpretability is. The error training level reflects when and how the error decreases. The method used in this model is exceedingly successful. Further application in each indicator can analyze the interpretation degree of the indicator to the

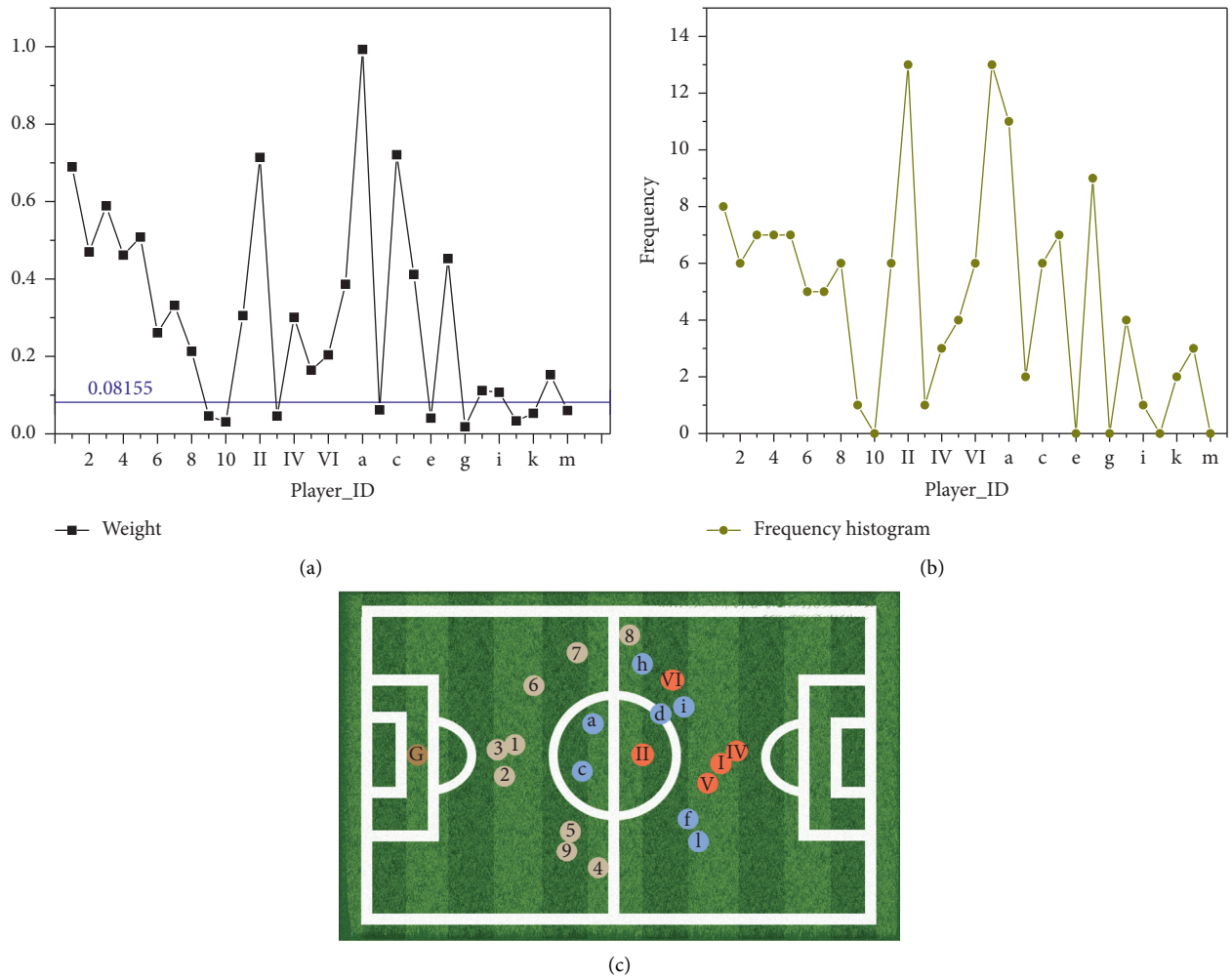


Figure 4: (a) Pass success times; (b) player frequency; (c) best players and positions.

Table 4: Pass success rate.

Player_ID	Sum_pass	Success_pass	Success rate	Player_ID	Sum_pass	Success_pass	Success rate
a	1526	1225	0.8028	VI	327	223	0.6820
II	1120	859	0.7670	l	242	134	0.5537
1	1090	851	0.7807	V	227	158	0.6960
c	1074	887	0.8259	IV	212	125	0.5896
3	934	727	0.7784	h	206	137	0.6650
5	829	625	0.7539	i	202	130	0.6436
G	777	473	0.6088	m	101	74	0.7327
4	772	569	0.7370	b	97	76	0.7835
2	718	580	0.8078	k	84	65	0.7738
f	702	508	0.7236	III	80	56	0.7000
d	660	497	0.7530	9	65	57	0.8769
7	601	408	0.6789	e	56	42	0.7500
6	475	322	0.6779	10	52	38	0.7308
8	382	263	0.6885	j	47	36	0.7660
I	362	238	0.6575	g	23	22	0.9565

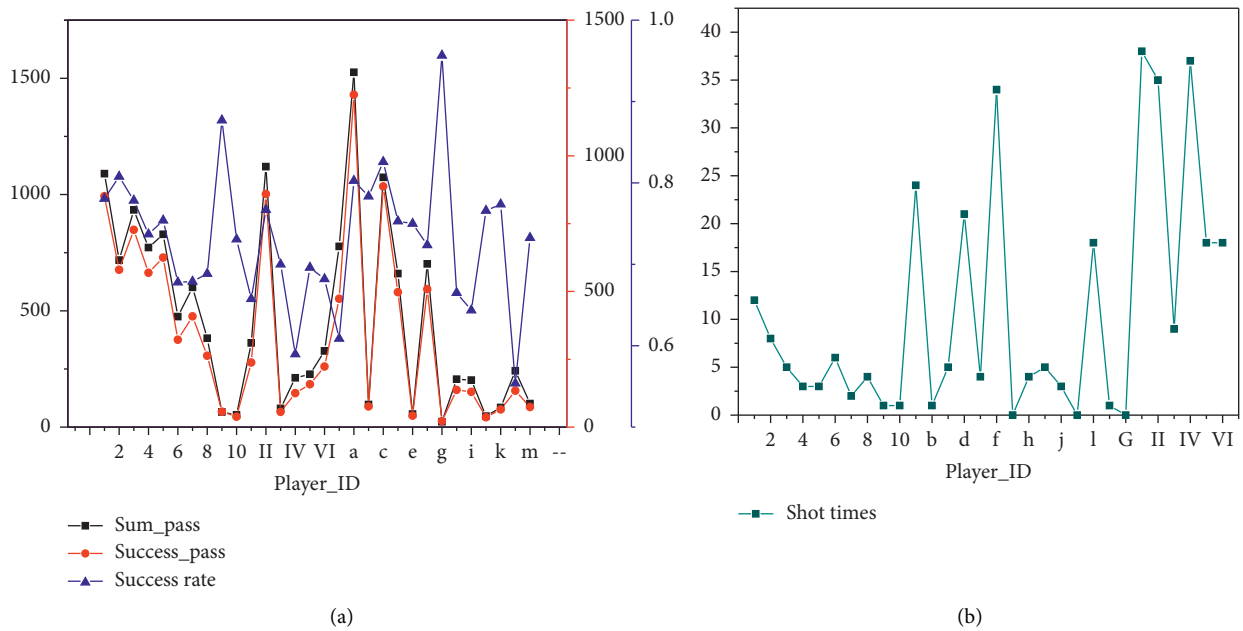
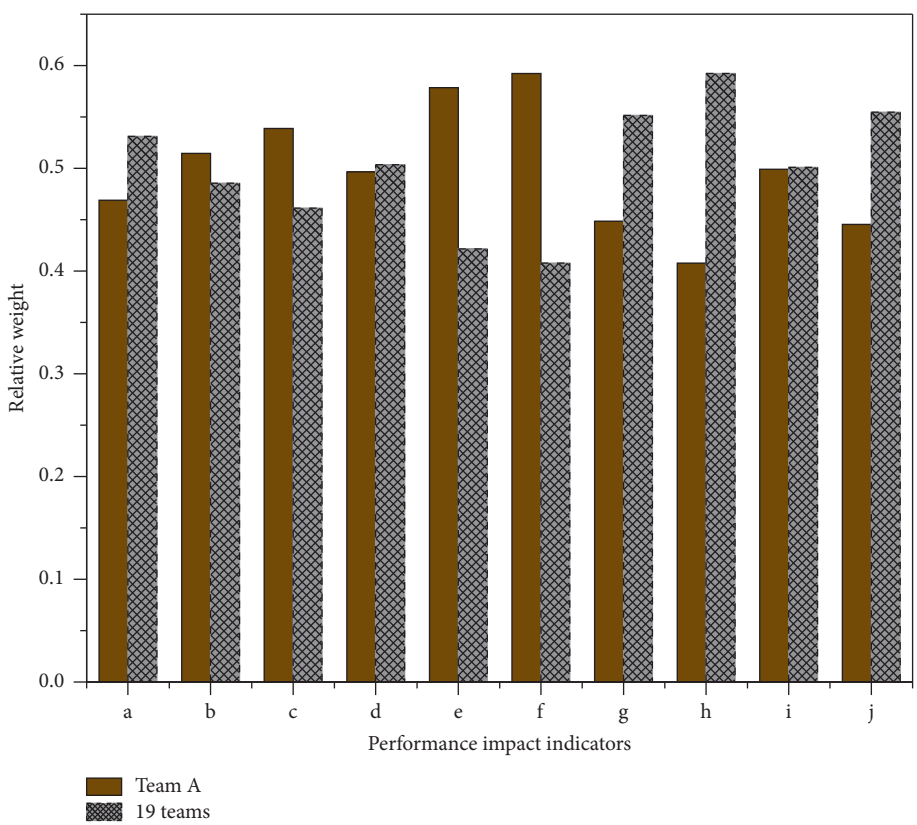


Figure 5: (a) Comparison of pass success rate and (b) shooting times.



Description of abscissa symbols					
Symbols	a	b	c	d	e
Indicators	Free kick	Duel	Foul	Goalkeeper leaving line	Offside
Symbols	f	g	h	i	j
Indicators	Save attempt	Pass	Shot	Others on the ball	Cross

Figure 6: Comparison of football indexes.

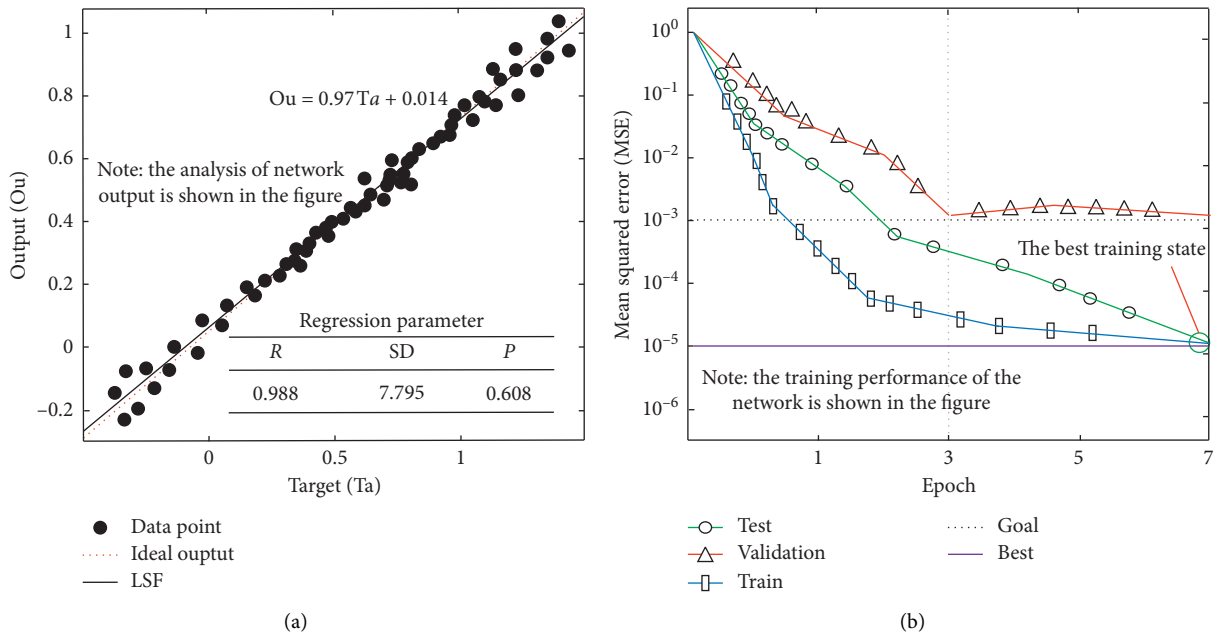


Figure 7: Regression level and the train performance of the BPNN. (a) The regression of network output target and (b) comprehensive performance of network training.

results, which can be used as the basis for performance evaluation of this level, and the specific results will be displayed in the result analysis.

Secondly, in the process of team-level analysis, it is necessary to assign values to indicators. Using entropy weight method and known data, it is not difficult to obtain the corresponding weight matrix:

$$W = [0.1389 \;\; 0.0767 \;\; 0.0370 \;\; 0.0575 \;\; 0.0663 \;\; 0.1889 \;\; 0.0886 \;\; 0.2154 \;\; 0.1308]. \tag{6}$$

By analyzing the matrix, the corresponding concrete results can be easily obtained.

Using the BP neural network method, the influence weight of each competition behavior on the results of the output layer of the competition in all competitions also can be easily obtained, as shown in Table 5.

Behavior analysis is an exceedingly successful explanation of the influence of behavior itself on the result of the game. Specifically, the factors that affect the number of successful passing are free kick, foul, pass, offside, and other on the ball; the factors that affect the result of the game are offside, other on the ball, pass, and shot; the main factors that affect the score of one's side are shot and pass; the main factors that affect the score of the opponent are shot and pass.

Finally, to facilitate the subsequent analysis, the weight value of the member level should be given. Shot, pass, offside, and duel are selected as the main influencing factors of member level, and the weight is $w = [0.3075 \;\; 0.3823 \;\; 0.1706 \;\; 0.1396]$. The method to determine the weight can be entropy weight method. This is because the gray level of the data is too large to get the weight matrix by normal factor analysis (Table 6).

Table 5: The result and analysis of the single factor.

Training input factor	Output
Free kick	[0.2933 0.0249 0.4593 0.9462]
Duel	[0.4082 0.3286 0.5368 0.3862]
Foul	[0.0539 0.7903 0.7230 0.9044]
Goalkeeper leaving line	[0.3670 0.4747 0.8556 1.0432]
Offside	[0.0144 0.8095 1.1139 1.0642]
Others on the ball	[0.5934 0.2505 0.6177 0.8342]
Pass	[0.8244 0.1504 1.0054 1.0893]
Save attempt	[0.3402 0.1329 0.4367 0.7990]
Shot	[0.9898 1.0153 0.9647 0.2937]

Table 6 shows the contribution of two factors to team performance evaluation, in which the weight of the team level is 0.8 and that of member level is 0.2. The results strongly suggest that, as a competitive sport, teamwork and interaction are far more important than individual performance.

At the team level, there are three main subfactors, namely, team adaptability, team flexibility, and team rhythm control. The weight of team rhythm control is 0.6236, which is the biggest subfactor affecting team level, followed by team flexibility and adaptability, whose weights are 0.2165 and 0.1608, respectively. It is easy to get such inspiration from the results that the rhythm control of a team in the game almost affects the outcome of the game, so it is very important to develop appropriate strategies to ensure the team's rhythm control of the game.

At the member level, the player's passing behavior and shooting behavior are the biggest subfactors affecting the member level, with a weight of 0.3823 and 0.3057, respectively. Offside behavior and duel behavior have less impact, with a weight of 0.1706 and 0.1396, respectively. Based on the analysis, Team A's players should pass more and duel less.

Table 6: The result and analysis of the single factor.

Target	Factor group	Subfactor	Subfactor weight
Team performance evaluation	Team level 0.8	Adaptability	0.1608
		Flexibility	0.2156
		Rhythm control	0.6236
	Member level 0.2	Shot	0.3057
		Pass	0.3823
		Offside	0.1706
		Duel	0.1396

Table 7: Description of code.

Code	1	2	3	4	5	6	7	8	9	10	G	I	II	III	IV	V
Player_ID	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	G1	F1	F2	F3	F4	F5
Code	VI	a	b	c	d	e	f	g	h	i	j	k	l	m	C	
Player_ID	F6	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	Clustering coefficient	

5. Conclusions

This paper proposed a new method for analyzing and modeling the performance of Team A, and the following four conclusions are obtained:

(i) The best lineup match is "4-4-2" by restoring the most commonly used lineup position of players in the season, using the means of network science and cross-validation with data to prove that Team A is a tactically conservative team.

(ii) A performance index evaluation model is established based on BP-(U-AHP) method to comprehensively evaluate the team. The conclusion is that Team A ought to pay attention to the importance of individual behavior to member level and the influence of factors including adaptability and flexibility for the strength of the team.

(iii) The conservative style of the team's game can be determined through the analysis of the game data, the best selection of the specific personnel of the team's on-site structural position can be obtained, and the best structural strategy guidance can be designed for the next season.

(iv) The performance of complex systems can be evaluated from three aspects: supervision rules, team performance, and member performance.

The construction process of this model reflects the application of group dynamics in actual combat. Through the construction of the football network, the thesis analyzes a series of internal and external influencing factors that Team A performs better than the other 19 teams in the field so that the advantages of the team can be better displayed and the effectiveness of the team can be fully played.

Appendix

The player indicator replaces the symbol as follows (Table 7).

Data Availability

The three datasets used in this paper are the "full event. csv," "passing event. csv," and "matches. csv," and they can be easily obtained from the following website with the extraction code FKq3, http://mail.qhu.edu.cn:9900/coremail/XT5/jsp/download.jsp?share_link=D9AAF303459B4E6F81544809F6A76EDA&uid=1720405027%40qhu.edu.cn.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

In this paper, three datasets are used as supplementary materials. The dataset contains the real-time information of Team A and 38 teams in the game, the result of the game, and the information of the successful pass. Because the information reflected in the dataset is relatively large, it is uploaded as an attachment. (*Supplementary Materials*)

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