Problem Chosen	2020	Team Control Number
D	MCM/ICM Summary Sheet	2017363

Exploring team strategy from football

Summary

Nowadays, competition is everywhere in human society. A success often depends on teamwork. Football is a competitive sport that tests teamwork extremely. In order to identify the network for the ball passing , quantify and formalize team performance indicators to help the Huskies team build better, we establish several models to solve these problems and finally extend to the team activities that are common in society.

For question 1, we analyze the data provied and establish a integrated football passing network. On the basis of the network topology diagram, we use social network analysis methods to establish network for the ball passing identification models , with the help of UCIENT, to identify network patterns from three levels: overall network, partial network, and individual network. After that, we use the structural hole analysis method to analyze properties such as location and structural hole to further identify Dyadic Configurations and Triadic Configurations in the network for the ball passing. Finally, we consider the influence of the time factor on the measurement of the network for the ball passing, and establish a dynamic social network evolution clustering model to identify the passing network in a deeper way through time evolution.

For question 2, we identify performance indicators that reflect successful teamwork and divide them into 5 criteria layers and 12 solution layer. Establishing a corresponding judgment matrix, we use MATLAB to calculate various indicators, and use AHP evaluation models to obtain important performance indicators to capture structural, configurational, and dynamical aspects of teamwork.

For question 3, based on the identification of huskies' passing network types and the analysis of their team cooperation performance indicators, we put forward suggestions for huskies on how to strengthen team building in the next season

For question 4, through the analysis of huskies, we summarize the dynamic process of football team cooperation and extend it to a wide range of team cooperation. According to IPO theory, we build a general conceptual model to study team performance.After analysis, we put forward the construction plan of excellent team from the perspective of each participant.

Keywords: Integrated passing network ; Structural hole ; Dynamic social network evolutionary clustering model ; Analytic hierarchy process; IPO.

Contents

1 Introduction

1.1 Problem Background

To improve the performance of football players is the starting point and ultimate goal of training and the objective analysis of football performance is the main basis for formulating training goals and evaluating training effects[1]. Passing is one of the most basic techniques of modern football.It is the basis of all the techniques and tactics in football match. The application of passing technology will directly affect the exertion of the team's skills and tactics and the results of the game[2].The academic circle has always paid more attention to the study of passing performance in football match, but most of the studies are mostly based on the participants, ignoring the relationship between the individuals. The research method mostly adopts the method of mathematical statistics to analyze the technical indexes such as pass frequency, pass success rate and pass type in the football match. The statistical indexes are lack of new ideas.With the arrival of the era of big data, the indicators of competition performance analysis are further refined, the understanding of the attributes and connections of technical data will be more and more in-depth, and the construction of indicator system will become more and more complex. The progress of scientific methods will inevitably bring a breakthrough in sports scientific research. The correct use of team scientific research methods can not only improve the quality of sports scientific research, but also effectively solve the theoretical and practical problems of team activities[9].

1.2 Restatement of the problem

We need to use the data given to build a suitable network for the ball passing, quantify and formalize the structure and dynamic characteristics of team success (or failure), explore how team dynamics throughout the game and season affect their success, and help identify specific strategies that can improve teamwork next season.

Our specific tasks are the following:

- Create a network for the ball passing between players, use the passing network to identify network patterns and explore other structural indicators and network properties of the whole game on multiple scales.
- Identify performance indicators that reflect successful teamwork (in addition to points or wins). Clarify whether strategies are universally effective or dependent on opponents' counter-strategies. Use the performance indicators and team level processes to create a model that captures structural, configurational, and dynamical aspects of teamwork.
- Use the insights gained you're your teamwork model to inform the coach about what kinds of structural strategies have been effective for the Huskies. Advise the coach on what changes the network analysis indicates that they should make next season to improve team success.
- Generalize our findings, say something about how to design more effective teams and put forward other aspects of teamwork would need to be captured to develop generalized models of team performance.

1.3 literature review

For this reason, some scholars have studied the cooperation and interaction in football teamwork. Football is a complex non-linear system[4], the performance of a team is not only affected by its own factors, but also depends on the level and play of the opponent. Simple statistics can not describe the game indicators and the relationship between the results more accurately. Therefore, more effective mathematical means are needed to complete the analysis of the game data. In the late 1970s, Gould and gatrell[5] put forward the concept of passing network related to football match, but unfortunately, the research only stayed in the concept. Until 2010, Duch[6] revealed the key information about the organization, evolution and performance of football teams and players through the method of network science, which opened a new situation of football scientific research. On this basis, grund[7]further studies the structure and central characteristics of the network, which confirms that teams with low degree of centralization and high degree of agglomeration in the game are more likely to win. Since then, more and more dynamic characteristics and important performance indicators in football games have been quantified, and the analysis of football game data has become more and more reasonable and diversified

However, the research on the influence of football team cooperation on victory is still in its infancy. Although some achievements have been made, there are still many complex factors to be studied. In this paper, we establish a new type of comprehensive football passing network , which combines the complex network analysis method and social network analysis method, and propose a new dynamic social network evolution clustering model. Based on the identification model, we also establish the analytic hierarchy process model of team cooperation performance indicators. In addition, we extend our model to adapt it to social cooperative activities.

1.4 Our work

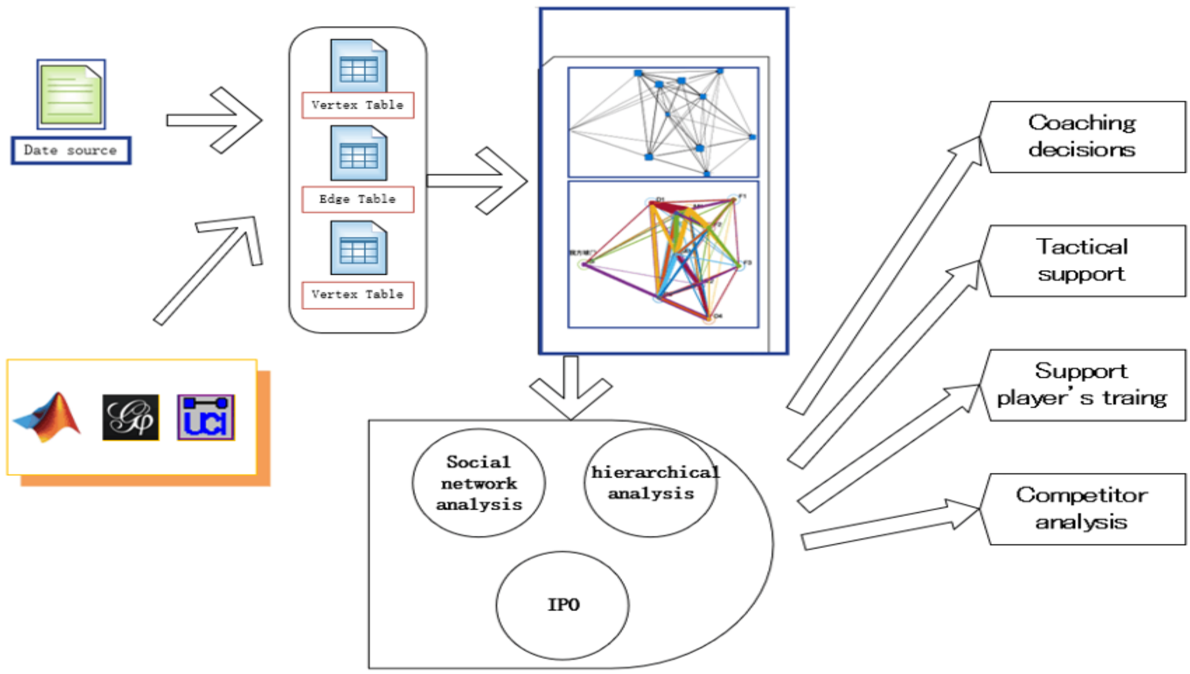

Figure 1: Our work

2 General Assumptions

- **We assume that the player's position in the game is determined by the average passing position.**In the data provided, the movement process of each player is not recorded, so we choose the average position to roughly represent their position.
- **We consider it a failure to pass when our players pass the ball to their opponents.**

- **It is assumed that the interaction between the selected indicators can be ignored, and in addition to these indicators, the impact of other indicators on the team's successful cooperation is ignored.**

3 Model Parameters

Table 1: notations

Symbol	Meaning
k_{in}	In degree
k_{out}	Out degree
O	Whether team cooperation is successful
C1	Team cohesion
C2	Effective cooperation of the team
C3	Distribution of player contributions
C4	Team internal coordination
C5	The tactics of the whole team
P1	The attitude of a team in various situations, such as headwinds
P2	Effectiveness of passing
P3	The way of passing
P4	The efficiency of attack defense conversion
P5	Scoring ability of team attacking players
P6	The choice of attack mode
P7	Set piece allocation
P8	The team's ability to seize opportunities
P9	The team's ability to create opportunities
P10	The strategy of the opponent
P11	Influence of site factors
P12	A strategy assigned by a coach to suit a team membe

4 Preparation of modeling model

4.1 Comprehensive football passing network

First of all, we use match 1 data between Huskies and opponent 1 to build our comprehensive passing network. Because passing is a one-way relationship, the original matrix is a directed multi value matrix. In order to reflect the two-way passing relationship between players, it is necessary to transform the original matrix into a symmetric matrix based on the average of the outgoing and incoming degrees. We import the original matrix into

However, considering the change of the position of the passing players on the field, it is not conducive to reveal the information of the team's organization mode by using this kind of passing network diagram, and the research on the team's performance is also one-sided. Therefore, we take the average value of all the receiving and passing coordinate data of each player in the game, and accurately locate each node according to the obtained coordinate position. and the comprehensive passing network topology map is obtained by combining the football passing network diagrams. (Fig2,Fig3).

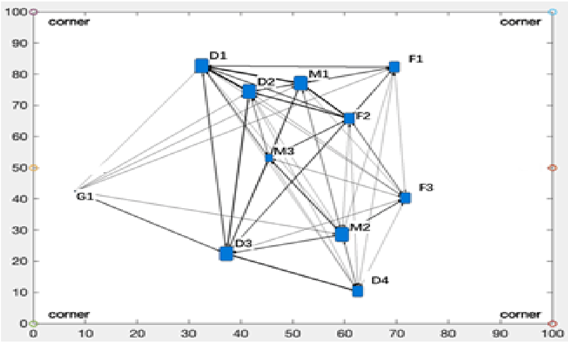

Figure 2: Huskies

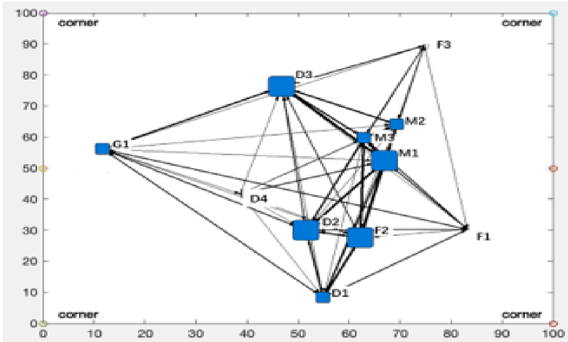

Figure 3: Opponent1

The players on the field are the nodes in the figure. The player number is marked beside the nodes. The more times the players pass the ball (the node degree), the larger the circle representing the nodes. The connection between the nodes represents the players' direct passing times. The more passing times, the thicker the connection. In order to facilitate the comparison between networks, if a player is changed, the new player will occupy the node of the previous player. In this way, we ensure that all networks have 11 participants, focusing on the structure of the whole network, rather than the performance of isolated participants. Our comprehensive passing network topology combines the concepts of average pass network and social network, which can better reveal the information of team organization and analyze diversified team performance. Therefore, we use the comprehensive pass network to sort out the data, and build a multi angle network identification model based on the comprehensive pass network.

4.2 Analysis of overall passing data

First, we counted the data of Huskies and its competitors in all competitions (38 games in total) this season, and compared four different network parameters of Huskies and its competitors (as shown in Figure 4). The four parameters are: (a) football passing times L, (b) shot times s, (c) goal times g, (d) pass success rate R. They are classic indicators of team performance. The left column in all the figures corresponds to the average of these indicators in all huskies competitions in the season, while the right column is the same indicator obtained for the opponent in the same competition. We always average the Huskies team on its own and all the other teams, because we just want to see the difference between Huskies and all the other teams. The green chart highlights statistically significant differences.

Note: We do not need to obtain and analyze the network structure of each team to calculate these 4 variables. Although some of them (i.e.the number of passes) affect the organization of the network.

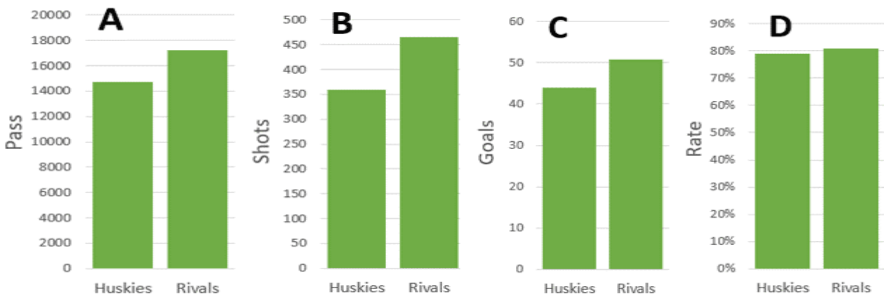

Figure 4: Opponent1

As shown in Figure 4a, Huskies 's passing times are lower than the average of competitors, and low passing times inevitably lead to a passing network with a link of lower weight. As we will see, this fact will have an impact on network parameters. In the Huskies team, the number of shots is also lower than the opponent's average (Fig 4b), resulting in a lower number of goals (Fig 4C), and Huskies 's passing success rate is slightly lower than the opponent's average (Fig 4D), resulting in a poor cumulative score during the analyzed game.

From the overall statistical data, we consider that Huskies team's performance is not very satisfactory. In order to give scientific and reasonable suggestions to the team to support the team's better development, we will first analyze the data of the first winning game, and establish a mathematical model to explore what factors lead to Huskies team's winning. Finally, we will bring in data from all fields to verify the adaptability of our model.

5 Social network analysis model

Social network analysis takes actors and their relationships as the research content,through the study of the relationship models between actors, it analyzes the structure of these models and their impact on actors and the whole group. Social network is a collection of social actors as nodes and their relationships, while football passing network is a collection of players and their pass cooperation. The isomorphism of passing network and social network suggests the possibility of quantitative research on pass network in football match by using social network analysis method.

Based on the comprehensive network topology, we use the social network analysis method to analyze the network indexes of two teams. In the social network analysis method, according to the network type, it can be divided into three levels: the whole network, the local area network and the individual network. The whole network analyzes the passing characteristics of the whole team, including the network density and distance; the local network analyzes the matching characteristics of the local passing, including the core edge structure and player faction; the individual network analyzes the position and role of the players in the passing network, the main analysis indicators are :the centrality, position equivalence and structural hole.

5.1 Integrated Network Analysis

5.1.1 Network density and network distance

Network density refers to the ratio of the actual number of connections and the maximum number of possible connections in the informal network. Network density can be used to measure the closeness of the relationship between network members. Both characteristics are very representative of the overall network characteristics, so we identify these two characteristics from the perspective of the team as a whole. When the whole pass network is a directed network, assuming that there are n players and the actual pass times are m, the maximum possible value of the total number of relationships in theory is $n(n-1)$, then the network density is $m/(n(n-1))$. Network distance refers to the length of geodesic between two players in the network. It can be used to measure the minimum number of intermediate people needed to get in touch with any two members in the network.

As shown in Table 2, in terms of network density and distance, the network distance between the two teams is about 1, all nodes are accessible, there is no player without passing, most nodes can be directly connected with other nodes, which indicates that most players have direct connection with passing.while in these two teams, Huskies 's network density is obviously higher, which shows Huskies players are more active in passing. It can be seen that Huskies' overall net of the two teams is more advantageous.

In addition, from the statistical results in Table 2, we can see that Huskies team has more passes, so we can infer that the ball control rate and pass success rate are higher than those of the opponent1 team, Huskies team has more opportunities to launch attacks, and Huskies team wins 1:0 in the end. However, it is not enough to analyze the passing network only from the overall network level. It is necessary to analyze the passing network of these two team from the individual network and local area network level, so as to make a reasonable explanation for the results of the game.

Table 2: Index of Passing Track Network of Huskies and Opponent1 Teams

Huskies					opponent 1				
network density	network distance	pass overall	pass average	goals	network density	network distance	pass overall	pass average	goals
3.3182	1.091	377	34.27	1	1.7636	1.263	189	17.18	0

5.2 local area network analysis

5.2.1 Core-edge analysis

From the definition of the core-edge structure, the core-edge analysis is essentially the agglomerative subgroup analysis. The players on the field are divided into two agglomerative subgroups, one is the core player group, the other is the edge player group. Its purpose is to simplify the complex network and focus on the key structure. Using $UCIENT6.2$, we analyzed the core and edge of the passing network of the two teams. The calculation results are as follows (Fig. 5, Fig. 6).

	6 M1	2 D1	3 D2	4 D3	5 D4	1 G1	7 M2	8 M3	9 F1	10 F2	11 F3
6 M1	1.000	12.000	5.000	2.000	2.000	2.000	2.500	8.500	3.000	12.000	1.500
2 D1	12.000		14.500	7.000	0.500	2.000	1.000	5.000	2.500	3.000	0.500
3 D2	5.000	14.500	2.000	12.000	0.500	1.500	1.000	5.500	1.500	7.500	0.500
4 D3	2.000	7.000	12.000		6.500	4.000	4.000	7.000	0.500	3.000	1.500
5 D4	2.000	0.500	0.500	6.500			5.000	2.000	0.500	2.000	1.000
1 G1	2.000	2.000	1.500	4.000		1.000	0.500		1.000		
7 M2	2.500	1.000	1.000	4.000	5.000	0.500		6.500	0.500	2.000	3.000
8 M3	8.500	5.000	5.500	7.000	2.000		6.500			5.000	1.500
9 F1	3.000	2.500	1.500	0.500	0.500	1.000	0.500			4.000	1.500
10 F2	12.000	3.000	7.500	3.000	2.000		2.000	5.000	4.000		3.500
11 F3	1.500	0.500	0.500	1.500	1.000		3.000	1.500	1.500	3.500	

Figure 5: Core-edge Analysis of Huskies

	1 G1	2 D1	3 D2	4 D3	10 F2	6 M1	7 M2	8 M3	9 F1	5 D4	11 F3
1 G1		1.500	2.000	3.500	0.500	1.000	0.500		1.500	1.000	1.000
2 D1	1.500	1.000	2.500	0.500	4.000	2.500	0.500	1.000	2.000	0.500	
3 D2	2.000	2.500		1.500	3.000	4.000	1.000	3.000	2.000	0.500	0.500
4 D3	3.500	0.500	1.500	1.000	2.000	5.500	3.000	2.500	1.000	1.000	2.000
10 F2	0.500	4.000	3.000	2.000		5.000	4.000	4.000	1.000	1.000	1.000
6 M1	1.000	2.500	4.000	5.500	5.000		3.000	4.500	1.500	2.000	1.500
7 M2	0.500	0.500	1.000	3.000	4.000	3.000	1.000	3.000		0.500	1.500
8 M3		1.000	3.000	2.500	4.000	4.500	3.000		1.500	1.000	2.000
9 F1	1.500	2.000	2.000	1.000	1.000	1.500		1.500			0.500
5 D4	1.000	0.500	0.500	1.000	1.000	2.000	0.500	1.000			
11 F3	1.000		0.500	2.000	1.000	1.500	1.500	2.000	0.500		

Figure 6: Core-edge Analysis of Opponent1

The core-edge structure in the football passing network shows that the passing between core players and core players, between core players and edge players is very frequent, but the passing times between edge players and edge players are relatively small. Therefore, the core player in the pass network is not necessarily the player with the most passes, but it must be a player with key node nature that can connect the edge players and other core players. We regard the core players as a "faction", and the edge players are mainly integrated into the passing network through football passing with the players in this "faction". In football games, the main responsibility of midfield players in the passing network is to connect the back field and the front field by passing and receiving the ball. The more reasonable core-edge structure should be that the core group midfield players account for a large proportion.

As shown in Fig. 5 and Fig. 6, Huskies has 1 middle field player and 3 back field players, while opponent1has 3 middle field players , 4 back field players and 1 front field player. Most of huskies' core players are concentrated in the backcourt, forming a core-edge structure with backcourt as the core and midfield and forecourt as the edge. This structure of absence of midfield players shows that most of huskies' passing is between midfield and backfield. When attacking, midfield players can not effectively connect the backfield and the front field. Most of the passing is stuck in the middle and back field, so it is less likely to create a threatening passing. In contrast, the core edge structure of opponent1 is more reasonable, with a large number of core players and the same proportion of core players in the front and back field. On the field, it can not only transfer the ball to the back field for defense, but also transfer the ball to the front field for attack, which is also consistent with the higher number of shots of opponent1. But the final result of the game was huskies winning, so we need to further explore the passing between each team member to give further answers.

5.3 Individual Network Analysis

5.3.1 Structural hole analysis

Structural holes have advantages in analyzing the relationship between a node and any other node in the network. By solving the two main dimensions (cohesion and structural allelism) that describe the existence of structural holes, we can further explore the Dyadic Configurations and Triadic Configurations in the network. Combined with the data obtained above, we use structural hole analysis to further explore the network mode in the passing network.

1. Binary matrix

With the help of social network analysis tool *UCIENT*, through a series of forms of data transformation (standardization, symmetry, binarization, etc.), we finally get the data of two teams. In order to make the level of player cooperation more clear, set the standardized relationship value to be greater than or equal to 0.05 (this value can better filter out some weak relationships), and carry out binary processing. Assuming that the value 1 represents a relationship, and 0 represents no relationship, the following figure is obtained (Figure 7, figure 8).

	G1	D1	D2	D3	D4	M1	M2	M3	F1	F2	F3
G1	1	0	0	1	0	0	0	0	1	0	0
D1	1	0	1	1	0	1	0	1	1	1	0
D2	1	1	0	1	0	1	0	1	1	1	0
D3	1	1	1	0	1	0	1	1	0	1	1
D4	0	0	0	1	0	0	1	0	0	0	1
M1	1	1	1	0	1	0	1	1	1	1	1
M2	0	0	0	1	1	0	0	1	0	0	1
M3	0	1	1	1	1	1	1	0	0	1	1
F1	1	1	0	0	0	1	0	0	0	1	1
F2	0	1	1	1	1	1	1	1	1	0	1
F3	0	0	0	0	0	0	1	0	1	1	0

Figure 7: Binary matrix of Huskies

	G1	D1	D2	D3	D4	M1	M2	M3	F1	F2	F3
G1	0	1	1	1	1	1	1	0	1	1	1
D1	1	1	1	1	1	1	1	1	1	1	0
D2	1	1	0	1	1	1	1	1	1	1	1
D3	1	1	1	1	1	1	1	1	1	1	1
D4	1	1	1	1	0	1	1	1	0	1	0
M1	1	1	1	1	1	0	1	1	1	1	1
M2	1	1	1	1	1	1	1	1	0	1	1
M3	0	1	1	1	1	1	1	0	1	1	1
F1	1	1	1	1	0	1	0	1	0	1	1
F2	1	1	1	1	1	1	1	1	1	0	1
F3	1	0	1	1	0	1	1	1	1	1	0

Figure 8: Binary matrix of Opponent1

According to the comparison of the data in the figure, any two players in the opponent1 team generally have a pass on the court, but Huskies' two-player pass is obviously not between any two players. From the passing network figure,We find that F1, F3, M2 and D4 in huskies team, which pass less than others, are in the front position. It can be inferred that huskies team adopts the one with closer passing at the back Way to keep the ball and rely on the front four players to attack, and this method is effective. However, there are many passing situations in the game, so we need to further explore the data.

2. Block model analysis

In order to further reflect whether there is structure allelism between players' passing relationships, a block model is constructed by cluster analysis. The so-called block model($_k lr$): it is to partition players in a network N into positions B_1, B_2 ,..., B_K, and there is a corresponding rule ϕ that divides players into different positions, that is, if player i is in position B_K, then ϕ (I) = B_k. $b_k lr$ was used to characterize whether there was a relationship between B_K and B_1 on the relationship X_r. If there is a relationship, $b_k lr$ = 1, otherwise 0. Block model has two main functions: one is to classify the players with structural allelism in the team to form different "positions", which can also be called "clustering". The second is to examine the relationship between classes. The network organization block model analysis is implemented for table 1, and the results are shown in Figure 9.

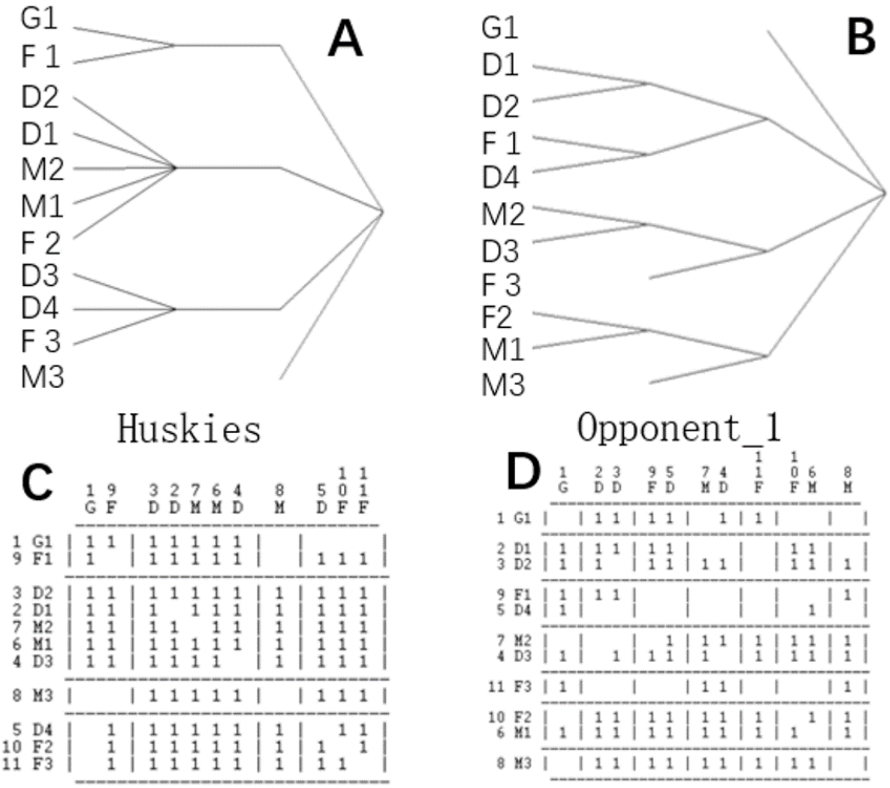

Figure 9: location allelism

As shown in Figure 9a and 9C, in the comprehensive football passing network, when the relationship strength is 0.05, huskies team has three classes with structural allelism, namely: Class 1 (G1, F1), class 2 (D2, D1, M2, M1, D3), class 3 (D4, F2, F3), and opponent team 1 (Figure 9b and 9D): Class 1 (D1, D2), position 2 (F1, D4), position 3 (m2, D3), position 4 (F2, M1). Because of the structural allelism between members in each class, members have strong cohesion, strong dependence on each other, natural binding force on each other, and it is difficult to form structural holes. Performance in the players is the influence of a single player on the court, the cohesion of the organization attack, these players often have strong personal ability, and have a higher position on the court. For the relationship between classes, the more the relationship between a certain class and other classes is established, the more advantage this position has in the network, the stronger the network control ability, and the easier it is to form a structural hole, which is reflected in the flexibility of a single player on the court, and these players usually have relatively strong mobility. It can be seen from the data that players of huskies team are easy to form on-the-spot combination with strong cohesion. On the contrary, there are multiple two person football passing combinations in opppnent1team without multi person passing cooperation. Although the two person combination of opponent1team is closely related, the number of players not in the cluster combination is large, and the overall team cohesion is not as good as huskies team.

	G1	D1	D2	D3	D4	M1	M2	M3	F1	F2	F3
G1	0.07	0.07	0.07	0.07	0.00	0.07	0.07	0.00	0.07	0.00	0.00
D1	0.02	0.00	0.04	0.04	0.03	0.04	0.04	0.03	0.04	0.03	0.03
D2	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
D3	0.02	0.04	0.04	0.00	0.03	0.04	0.04	0.03	0.04	0.03	0.03
D4	0.00	0.05	0.05	0.05	0.00	0.05	0.05	0.04	0.04	0.05	0.05
M1	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
M2	0.02	0.04	0.04	0.04	0.03	0.04	0.00	0.03	0.04	0.03	0.03
M3	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.05	0.05
F1	0.03	0.05	0.05	0.05	0.04	0.05	0.05	0.00	0.00	0.04	0.04
F2	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.00	0.05
F3	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.05	0.00

Figure 10: structural holes of Huskies

	G1	D1	D2	D3	D4	M1	M2	M3	F1	F2	F3
G1	0.00	0.07	0.09	0.09	0.05	0.07	0.00	0.00	0.06	0.00	0.04
D1	0.05	0.07	0.08	0.00	0.02	0.07	0.00	0.03	0.06	0.06	0.00
D2	0.04	0.05	0.00	0.05	0.02	0.06	0.02	0.05	0.04	0.05	0.00
D3	0.04	0.00	0.05	0.00	0.02	0.06	0.05	0.06	0.02	0.05	0.04
D4	0.07	0.04	0.06	0.06	0.00	0.10	0.03	0.04	0.00	0.05	0.00
M1	0.02	0.03	0.05	0.05	0.03	0.00	0.04	0.05	0.02	0.05	0.02
M2	0.00	0.00	0.03	0.07	0.02	0.07	0.07	0.07	0.00	0.07	0.05
M3	0.00	0.02	0.05	0.06	0.01	0.07	0.05	0.00	0.03	0.06	0.03
F1	0.07	0.09	0.11	0.05	0.00	0.06	0.00	0.07	0.00	0.05	0.00
F2	0.00	0.04	0.06	0.06	0.02	0.07	0.05	0.07	0.02	0.00	0.02
F3	0.06	0.00	0.00	0.16	0.00	0.08	0.10	0.10	0.00	0.05	0.00

Figure 11: structural holes of Opponent1

The differences between structural allelism and class relations further promote the formation of structural holes. According to the construction principle and calculation program of the structural hole, the constraint degree of the two teams in the passing network is obtained (see Figure 10 and Figure 11). As shown in the figure, 1) the sum of constraint degrees of each player (except goalkeeper) in team O is greater than the sum of constraint degrees of team H, and the constraint degree is inversely proportional to the number of structural holes. so the number of structural holes in team O is less than that in team H, indicating that the more times of mutual cooperation in team o, the greater the value of mutual cooperation. 2) Except for the goalkeeper, no player in team h has a constraint value greater than 0.05 for another player, while the constraint value of team O is generally high, even higher than 0.16, indicating that each player of team O has fewer structural holes and the enthusiasm of team O is less than that of team H.The player's on-the-field activeness has a great influence on the success of team cooperation and the final victory of the game, so it finally leads to the defeat of opponent1 team.

6 Temporal evolution of the network metrics

6.1 18-Segmented dynamic passing network

Before we make any explanation, we must make clear two problems: 1) behind the difference of network parameters, there is not only the number of passes; 2) only looking at the average value of network indicators is not enough. What's more, social network analysis has its own limitations. Obviously, social network analysis uses the statistical data of the whole game, and only pays attention to the structure and characteristics of the network. The research on the changes of node position and network characteristics with time in the network is not involved. Therefore, simply using social network analysis to study the performance of the football match will easily lead to the research divorced from the reality, deviation and misunderstanding. Only considering the influence of time factor on network measurement, we can better explain the problem by observing the changes of some indicators over time. On the one hand, we

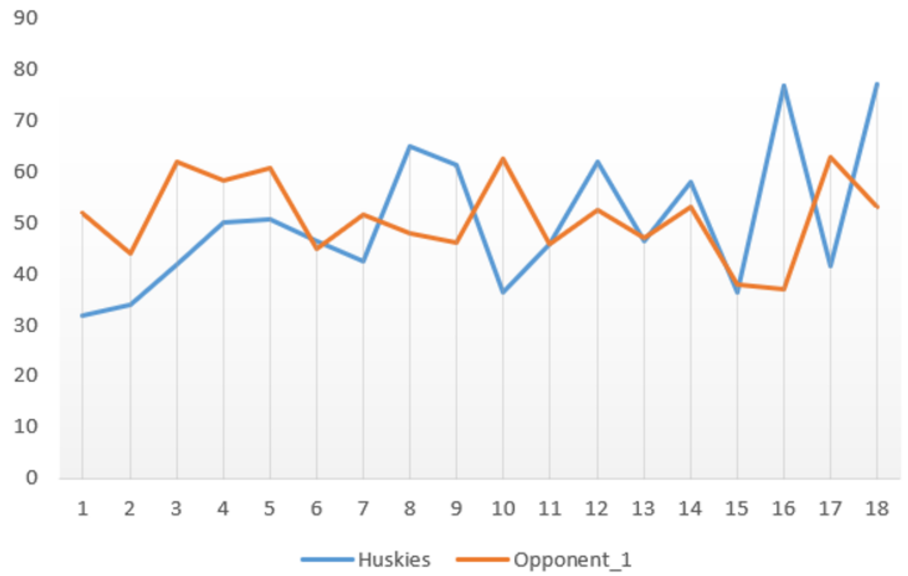

Figure 12: < x > average coordinates of each time period of the two teams

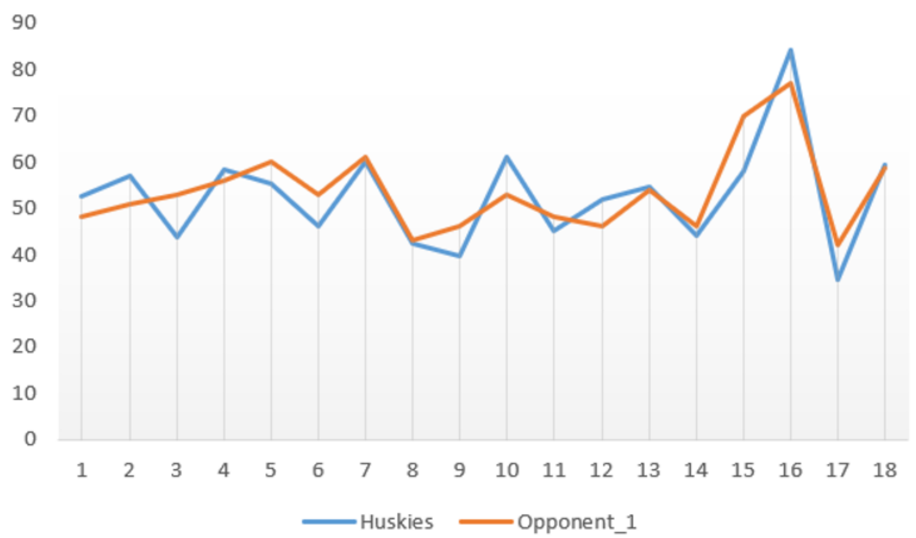

Figure 13: < y > average coordinates of each time period of the two teams

define the passing network as a non static entity, which changes in time. We will analyze the changes of its parameters. On the other hand, we will exclude the importance of passing times so as to focus only on the topology of the network. Therefore, we obtain 18 18 stage football passing networks by the following ways: (I) a ball game is divided into 18 small time periods (each time period is about 5 minutes, which can accurately cover the process of organizing an attack) (II) in each time period, we calculate the average pass position of each team. We get the time-varying graph of the average position of the two teams in the whole match (Figure 12, figure 13). It can be seen from the figure that the two teams usually look for attacking opportunities in the midfield. By comparison, team o has a higher < x > value, which shows that the advantage of opponent team 1 in the front field is greater. This is also due to the analysis above that the flexibility of the two team combination can create more breakthrough opportunities. In huskies' data, there are obvious differences in 8 and 9 segments compared with other data. Obviously, there are many times of passing in front field and on the right side. It can be inferred that huskies has launched a fierce attack in the middle of the whole game, and the team is more inclined to attack on the right side.

6.2 Dynamic social network evolution clustering model concept

In order to make the dynamic expression of network degree more diversified, the dynamic network is generated by GEPHI simulation and used to show the dynamic characteristics of nodes and edges in the dynamic network. We use the dynamic social network evolution clustering model to interpret the dynamic process of football cooperation.

G = < G_1, G_2... G_T > represents a dynamic passing network, in which G_t=(V_t,B_t) is a graph composed of player set $v_t \subset$ V's relationship at time Bt, also known as dynamic time snapshot, and dynamic network snapshot at time t constitutes dynamic passing network G.However, the dynamic network evolves with the change of topological structure over time. In order to realize the precise identification of complex passing network, it is necessary to find some statistical characteristics, which is an important aspect of understanding complex network. There are many geometric quantities describing its structural characteristics, among which degree distribution, average path length and aggregation coefficient are the three most basic statistical characteristics.

A graph G consists of a vertex (player) set V and an edge (pass) set B, where V=v_1,v_2,...,v_n represents the set of vertices,B={b_ij(i,j)∈S $[1,\ldots,n]^2$}represents the set of edges, b_ij is defined as expression (1).

$$b_{ij} = \begin{cases} 1 & , \quad \text{pass} \\ 0 & , \quad \text{no pass} \end{cases} \tag{1}$$

In a directed graph, the degrees of vertices are divided into in degrees k_in and out degrees k_out.

$$k_{in} = \sum_{i=in} b_{ij} \ , \ k_{out} = \sum_{j=out} b_{ij}$$

In the network, a distribution function P (k) is used to represent the degree distribution of nodes, such as expression (2), which refers to the probability that the degree of a randomly selected node is exactly k. Use <k> to represent the average degree of the network.

$$P(k' \geq k) = \sum_{k'=k}^{\infty} p_k \tag{2}$$

The aggregation coefficient CI is the ratio of a player's actual passing number and all sides. If the degree of a node is K_i, the actual number of sides is B_i, and all sides in the network are k_i (K_i-1), then the aggregation coefficient is formula (3).

$$C_i = \frac{2B_i}{k_i(k_i - 1)} \tag{3}$$

The average of the focal coefficients of all nodes is the focal coefficient of the whole network. In every reasonable period of time, the focus coefficient of all players on the field can identify the dynamic changes of the team's passing enthusiasm and player's activeness.

We design an evolutionary clustering model. First of all, the first k clustering centers with large degree of selection are used for initial clustering of the dynamic network snapshot at the first time, and the first time is set as the current time to calculate the network changes of the snapshot at the current time and the snapshot at the next time. When the network change is greater than the given threshold, we will re cluster the nodes of the next snapshot; when the network change is less than or given threshold, we will adjust the current clustering results to obtain the clustering results of the next snapshot.

If the clustering results are adjusted at the current time, it is easy to establish the corresponding relationship between the two adjacent time clustering results, so as to determine the clustering evolution time; if the clustering results are re clustered, it is necessary to analyze the corresponding relationship between the two adjacent time clustering results to determine the evolution event. Then the following snapshot is taken as the current time, and the above steps are repeated until all the time has been analyzed. The clustering results of all the snapshot and the evolution of the clustering results in the whole dynamic network evolution process are obtained. According to the evolution, we can more clearly identify the changes of players in different periods. In this way, we can not only identify the mode of organizing attack, changing defense or keeping control of the ball, but also identify which players are the main players in this mode.

7 AHP model for performance metrics and team level processes

Based on the identification network, we choose the analytic hierarchy process (AHP) to establish a model to solve problem 2. AHP is a simple, flexible and practical method for quantitative analysis of qualitative problems. It fits us to further quantify and formalize the structure of the team's success (and failure) and team level processes, providing Huskies with the basis for selecting the best solution.

7.1 Establish hierarchical structure and evaluation system

We propose 17 performance indicators related to successful team cooperation. According to the common characteristics and characteristics of these factors, we determine the correlation and subordination relationship among these factors, and divide them into objective layer, criterion layer and plan layer. In the end, we obtain the hierarchical structure of 5 criterion layers and 12 plan layers (fig14).

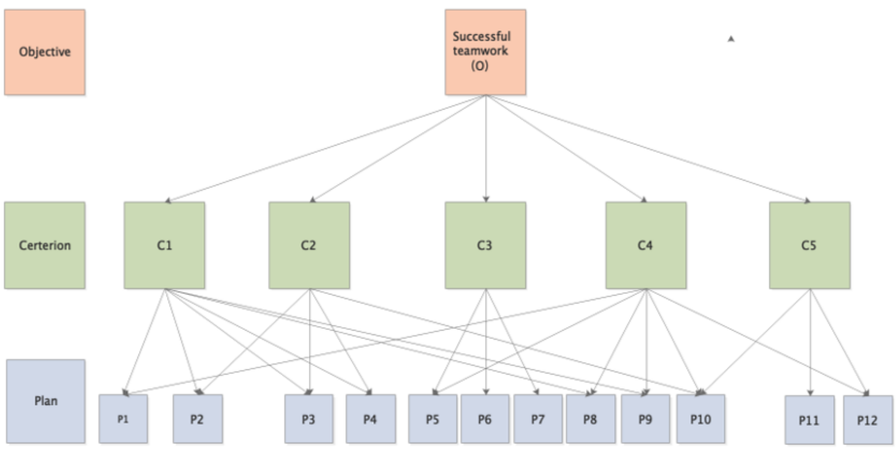

Figure 14: AHP structure diagram

7.2 Establish the judgment matrix

We use the nine-point scale method to determine the Aij in the judgment matrix. Based on the data provided and the analysis of football matches in many football analysis articles, we finally determine the judgment matrix among various indicators after repeated studies.

Table 3: The scale and definition of the nine point system

Scale	Meaning
1	two factors are of equal importance
3	one factor is slightly more important than the other
5	one factor is significantly more important than the other
7	one factor is more important than the other
9	one factor is much more important than the other
2,4,6,8	The median of the above two adjacent judgments
Reciprocal	A compared to B if the scale is 3, then B compared to A is 1/3

7.3 Consistency check

Before calculating the weight, we calculate the consistency index CI for each judgment matrix, find the corresponding mean random consistency index RI, and calculate the consistency ratio CR of each judgment matrix, so as to test the reliability of our judgment matrix.

Consistency indicator:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4}$$

Consistency ratio:

$$CR = \frac{CI}{RI} \begin{cases} < 0.1, \ Consistent \\ \geqslant 0.1, not\ consistent \end{cases} \tag{5}$$

Table 4: Average random consistency index RI

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54	1.56	1.58	1.59

CR < 0.1 of all judgment matrices can be obtained from the consistency test results. It can be considered that the consistency of judgment matrix is acceptable, and there is no need to modify the judgment matrix.

7.4 Calculate the weight of each index

(1) arithmetic average value method:

We normalize the judgment matrix in terms of columns. Then we add the normalized columns (sum by row), and finally divide each element of the resulting vector by n to get the arithmetic average weight vector.

$$\omega_i = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{6}$$

(2) geometric average method:

We multiply the elements of a by rows to get a new column vector. Then we open each component of the new vector to the nth power. Then we normalize the column vector, and finally we get the weight vector of the geometric average method.

$$w_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{k=1}^{n}\left(\prod_{j=1}^{n} a_{kj}\right)^{\frac{1}{n}}}, \quad (i = 1, 2, \cdots, n) \tag{7}$$

(3) eigenvalue method:

We calculate the maximum eigenvalue of matrix A and its corresponding eigenvectors, and then normalize the eigenvectors to obtain the weight of the eigenvalue method.

Due to the space, we put the judgment matrix and its weight index table in the appendix.

7.5 Evaluation results of each performance indicator

Finally, according to the proportion of each performance indicator calculated, we sort and comprehensively analyze the indicator, the results are shown in table 5. (for the explanation of each index in Table 5, please refer to the chapter of model parameters.)

Table 5: Average random consistency index RI

Evaluation index of team cooperation success	Proportion
P1:	4.72%
P2:	24.36%
P3:	7.06%
P4:	16.42%
P5:	1.32%
P6:	2.96%
P7:	1.63%
P8:	4.41%
P9:	7.39%
P10:	8.23%
P11:	1.60%
P12:	19.91%
P2 > P12 > P4 > P10 > P9 > P3 > P1 > P8 > P6 > P7 > P11 > P5	

As can be seen from the data in table 5, the five indicators are significant: the effectiveness of passing, the strategy developed by the coach, the efficiency of offensive and defensive transformation, the opponent's strategy and the team's overall ability to create opportunities. The coach's strategy which is suitable for the team members has a greater impact on the establishment of excellent teams than the opponent's strategy. This feature is also consistent with the phenomenon that each team member can achieve better performance if he or she gives full play to his or her characteristics in reality. This shows that the strategy made according to the characteristics of his or her own players is generally effective, and the strategy needs to be adjusted if he or she occasionally meets a stronger opponent. After the weight of each index has been determined, the training and organization management optimization suggestions put forward by us in combination with the recognition of huskies passing network are more convincing.

8 Optimization suggestions for huskies team

We used the insights we gained from the teamwork model to inform coaches which form of structure (contact network structure of question 1) strategy works for Huskies. The network analysis shows that they should make changes to improve the team's success in the next season(Success factors in contact question 2).

8.1 Effective structural strategies for the Huskies

Based on the passing network analyzed in the first question, and in relation to Huskies team performance, we explain that the following structural arrangements are valid for Huskies at three levels: overall, local and individual. 1. Network structure of overall agglomeration.

According to the topology map of the integrated passing network initially established and the four classic indexes of huskies, i.e. L, s, G and R, huskies team has high network density, strong players' activity and more active passing interaction among players. In addition (table 2), the Huskies passed more, had more chances to start attacks, and won 1-0. We therefore recommend that Huskies try to form a low centralisation and high concentration of the overall passing network. In the passing network with high density and short distance, there are direct passing connections between most players. All players can actively participate in passing and catching the ball, and further improve the passing quality, so that the passing network can flow more smoothly. On the other hand, H's opponents had relatively few players who connected the passes together, and the excessive passing depended on a few players, while the poor passing quality of other players affected the team's passing fluency.

2. Reasonable core - edge structure

The core player in the passing network is a player who can connect the edge player with other core players and has the key node nature. The core player is regarded as a "faction", and the edge player mainly passes the ball with the players in this "faction". The main responsibility of midfield players in the passing network is to connect the back field and the front field by passing and receiving the ball. We suggest that midfield players should have a high proportion in a more reasonable core edge structure. For example, in the time evolution of the passing network structure of team H (see figure 0), both teams are active in the midfield to find opportunities for attack. In contrast, the value of opponent1 team $< x >$ is greater and its advantages are greater. This is due to the flexibility of the combination of the team's forward and midfield, midfield and guard to create breakthrough opportunities. Forward and midfield, midfield and guard cooperate tacitly, establish a reasonable core edge structure, players in different positions cooperate with each other, occupy the ball right, midfield players take over the back field, and gradually advance the ball to the front field.

3. Efficient clustering structure

In question 1, we identify the dyadic and triadic configurations of team Huskies' passing. (Dyadic Configurations: relationships involving players. Triadic Configurations: relationships involving groups of three players.) The Triadic Configurations allow a passing network to act as a "hub" that connects players on the field and controls the pace of the team's game. We suggest to build more on-the-spot combination with strong cohesion. From the passing network chart, we find that the F1, F3, M2 and D4 positions of huskies team with less passing with other people are in the front, and adopt the way of close passing at the back to keep the ball right and rely on the four players in the front to launch the attack. The perfect structure can continue to be used for mutual cooperation.

(1) Key items of individual training

The key factors for the success of team cooperation on the pitch are team cohesion and team internal coordination, among which the most important indicator is the effectiveness of passing. In a game, invalid passing will give the opponent the chance to react and even create opportunities for the opponent. Therefore, in normal training, we should simulate the actual competitive state on the court, and strengthen the tacit understanding and cooperation of passing between players through some simulation methods. Huskies should set up a suitable passing method for each player, gather the whole team and form a closer network. At the same time, it is necessary to strengthen the physical strength of players. From the analysis of the given data, we can get the mobile activity of normal teams concentrated in the first half. By strengthening the physical strength, we can extend the effective movement time of players, so as to improve the effectiveness of passing.

(2) Strategy formulation

Before the game, the coach should have a more comprehensive evaluation of the other team's various factors, including: the opponent's preferred strategy, the opponent's team core, and the other team's strengths.We should also take into account the other side's analysis of our possible strategy, choose a global optimal starting lineup and tactical distribution.At the beginning of the game, the coach of the other side is likely to realize the control of our tactics through the adjustment of the lineup. It is very important to make a proper response according to the strategy of the other side. The coach needs to have a deeper understanding of his team, try to control his team from the perspective of the opponent, and make some effective solutions to strive for the initiative on the field.

(3) Internal cohesion of players

The coach should instill the team concept into the players and establish a more comprehensive overall view of the game, rather than being limited to individual play. This requires that the team has a relatively perfect reward and punishment measures. Only when the players gather together, can they maximize the passing mode and attack defense conversion mode they usually train on the field.

9 Teamwork conceptual model

Through the previous analysis, we can summarize the team's performance into the following categories: team structure, team environment, players' strategic position, passing interaction process, the victory of the game, and the improvement of players.In daily life, the solution of social problems more and more involves team problems. How to build an effective team is very important for the development of any field in the future. Next, we will build a common model of other team performance in real life based on team cooperation analysis to show how to design more effective teams.

We regard all cooperation teams as composed of members, objectives and connections[] ref8 which are input, process and output in the whole cooperation process, thus forming a simple IPO system (see table 15). According to the idea of I (input) - P (process) - O (output), we analyze the cooperation process in real life, and get the analysis framework as shown in figure 15. Input refers to the initial state of the team, including team structure (complementary skills of members, team preference), team environment (working mechanism and cooperation rules), team work requirements (task nature); process refers to the task execution process (work sharing, cooperation tacit understanding) and emotional interaction process (enthusiasm, team cohesion, interpersonal relationship) in the team Relationship, trust, communication and coordination); output is the part of team task completion quality, satisfaction of members and self-improvement. We will further refine the above analysis parameters to the direct

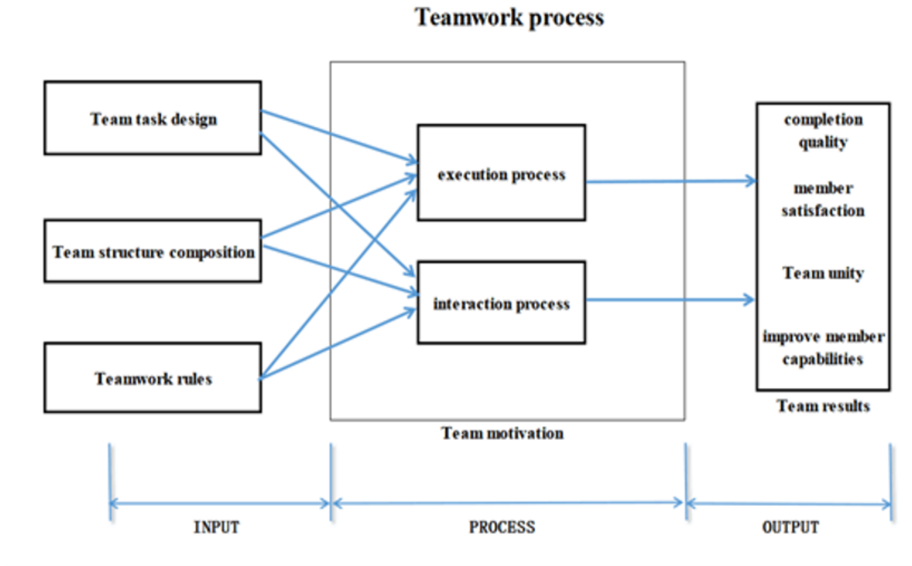

Figure 15: IPO structure diagram

participants in the team cooperation process, namely: team members, management and opponents (uncontrollable factors, not considered temporarily). Give the goal of each type of participants in an effective team.

For the team members, 1) the team members should carry out appropriate training, and the excellent members of the team should have the responsibility to help coordinate the skills of the team members. 2) the players should cooperate and coordinate, find opportunities and solve problems in the process of task execution. 3) the objectives should be clear, achieve the consistency between personal objectives and organizational objectives, and have a certain degree of enthusiasm.

For the management, 1) the management shall grant certain authority to the subordinates and make clear the tasks; 2) the management shall check and monitor the implementation of the objectives and the completion of the phased objectives, and correct the deviation in the process, and reasonably select and transfer the team members if necessary; 3) the management shall provide the team with various resources necessary for the completion of the work, but does not attempt to control it. 4) Have a set of measurement system to evaluate the overall performance of the team, and evaluate each team task.

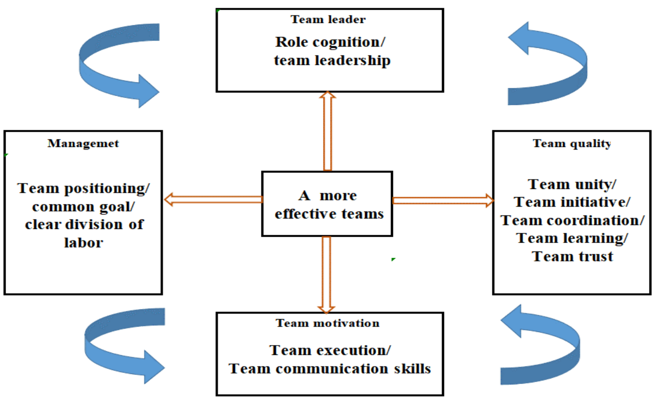

Figure 16: evaluating indicator

We provide a matching evaluation performance method for the proposed suggestions, and put forward the indicators to be understood by the evaluation team (as shown in the figure above). By weighting each index, we can analyze the effectiveness of a cooperation.

10 the stability analysis

In the AHP analysis, in order to ensure the stability of the final results, we use the arithmetic average method, the geometric average method, the eigenvalue method to calculate each weight and their mean value, so that the conclusions are more stable. And we test the consistency of all judgment matrices, and the consistency proportion of all judgment matrices can be accepted, so the results in AHP analysis have good stability.

11 strengths and weaknesses

Advantages

1. The results in this paper are presented in the form of many charts, which are clear and concise and have strong ornamental value.

2. In the process of evaluation and analysis, many influencing factors are taken into account, and the levels of all elements (including non quantitative and quantitative) are established, which clearly shows the relationship between each layer, each criterion and each element.

3. This paper analyzes the commonness of passing network and social network, uses the theory of structural hole in sociology to explain the passing relationship of players, and the solution is ingenious in conception, while maintaining the preciseness of thinking

4. It is innovative to establish a dynamic social network evolution clustering model to track the changes of network mode.

5. The results of problem solving are used in ucient software and MATLAB software, which makes the results have good accuracy and credibility.

Weakness

1. In the first problem, the average value of the passing position coordinates is used to represent the player's position on the field, which is idealized and ignores the error.

2. In the period near the end or low ball control rate, the number of passes is small, so the location of 18 segment network for this period of time is not accurate

References

[1] Zhao gang,Chen chao. Research on the research method and evaluation index system of football match performance[J].China sport science,2015(4):72-81.

[2] Qu xiaoguang. A study on the characteristics of technique and tactics of Chinese, American and Norwegian women's football teams[J]. China Sports Science and technology,2001,37(8): 26-9.

[3] Huang hansheng. Methodology exploration of sports science research: Based on the investigation and analysis of 300 doctoral theses in Chinese Sports Science[J].China sports science,2009(9):3-17.

[4] Perl J. A neural network approach to movement pattern analysis [J]. Human Movement Science, 2004, 23(5):605-620.

[5] Gould,P.& Gatrell,A.A structural analysis of a game: The Liverpool vs manchester united cup final of 1977.Soc. Netw. 2, 253–273(1979).

[6] Duch J., Waitzman J. S., Amaral L. A. Nunes. Quantifying the Performance of Individual Players in a Team Activity [J]. Plos One, 2010, 5(6): e10937.

[7] Grund T. U. Network structure and team performance:The case of English Premier League soccer teams [J].Social Networks, 2012, 34(4): 682-690.

[8] Lipnack J.,Stamps J..Virtual teams: reaching across space,time, and organizations with technology[M].New York:John Wiley and Sons.1997.

[9] Lowe D G. Distinctive image features from scale-invariant keypoints, International journal of computer vision, 2004, 60(2): 91-110.

Appendix

Appendix A: Judgement matrixes

We will show our judgement matrixes.

Table 6 : Judgment matrix between O and C

O	C1	C2	C3	C4	C5	Wi
C1	1	2	5	4	3	0.4221
C2	1/2	1	4	2	1	0.211
C3	1/5	1/4	1	1/3	1/4	0.0548
C4	1/4	1/2	3	1	1/2	0.1160
C5	1/3	1	4	2	1	0.1960
λmax： 5.0982 CR： 0.0219<0.1						

Table 7: The weights between O and C

count	geometry	feature	average
0.4207	0.4208	0.4249	0.4221
0.2106	0.2131	0.2094	0.2110
0.0556	0.0540	0.0548	0.0548
0.1171	0.1156	0.1154	0.1160
0.1960	0.1965	0.1955	0.1960

Table 8 : Judgment matrix between C1 and P

C1	P1	P2	P3	P4	P8	P9	wi
P1	1	1/5	1/3	1/4	1/2	1/2	0.0557
P2	5	1	3	2	4	2	0.3406
P3	3	1/3	1	1/4	1	1/2	0.0990
P4	4	1/2	4	1	3	2	0.2620
P8	2	1/4	1	1/3	1	1/2	0.0896
P9	2	1/2	2	1/2	2	1	0.1531
λmax： 6.1699 CR = 0.027 < 0.1							

Table 9: The weights between C1 and P

count	geometry	feature	average
0.0564	0.0550	0.0556	0.0557
0.3392	0.3419	0.3408	0.3406
0.1010	0.0970	0.0989	0.0990
0.2612	0.2615	0.2632	0.2620
0.0894	0.0906	0.0889	0.0896
0.1528	0.1540	0.1526	0.1531

Table 10 : Judgment matrix between C2 and P

C2	P2	P3	P4	P10	Wi
P2	1	3	2	4	0.4730
P3	1/3	1	1/2	1	0.1365
P4	1/2	2	1	2	0.2539
P10	1/4	1	1/2	1	0.1365
λmax： 4.0866 、 CR = 0.0324 < 0.1					

Table 11: The weights between C2 and P

count	geometry	feature	average
0.4725	0.4729	0.4737	0.4730
0.1367	0.1365	0.1364	0.1365
0.2541	0.2541	0.2535	0.2539
0.1367	0.1365	0.1364	0.1365

Table 12 : Judgment matrix between C3 and P

C3	P5	P6	P7	Wi
P5	1	1/3	1/2	0.1635
P6	3	1	2	0.5394
P7	2	1/2	1	0.2971
λmax： 3.0092、 CR = 0.0088 < 0.1				

Table 13: The weights between C3 and P

count	geometry	feature	average
0.1638	0.1634	0.1634	0.1635
0.5390	0.5396	0.5396	0.5394
0.2973	0.2970	0.2970	0.2971

Table 14 : Judgment matrix between C4 and P

C4	P1	P5	P8	P9	P10	P12	wi
P1	1	5	4	3	2	1/3	0.2041
P5	1/5	1	1/2	1/3	1/5	1/7	0.0364
P8	1/4	2	1	1/2	1/4	1/6	0.0539
P9	1/3	3	2	1	1/2	1/8	0.0798
P10	1/2	5	4	2	1	1/6	0.1399
P12	3	7	6	8	6	1	0.4858
λmax = 6.2902、 CR = 0.0462 < 0.1							

、Table 15: The weights between C4 and P

count	geometry	feature	average
0.2018	0.2095	0.2011	0.2041
0.0377	0.0355	0.0360	0.0364
0.0561	0.0529	0.0526	0.0539
0.0817	0.0801	0.0777	0.0798
0.1437	0.1384	0.1377	0.1399
0.4790	0.4835	0.4949	0.4858

Table 16 : Judgment matrix between C5 and P

C5	P10	P11	P12	Wi
P10	1	3	1/5	0.1900
P11	1/3	1	1/7	0.0818
P12	5	7	1	0.7282
λmax = 3.0649 、CR = 0.0624				

Table 17: The weights between C5 and P

count	geometry	feature	average
0.1932	0.1884	0.1884	0.1900
0.0833	0.0810	0.0810	0.0818
0.7235	0.7306	0.7306	0.7282

Appendix b:

Due to the page limit and file limit, we can not provide every script of each simulation because they have slight differences to meet different task requirements. However, the codes of main part of our model stays the same. The following script is one version consists of all system described in our paper. Readers may modified few lines to get all the simulations mentioned in our paper.

calculate.m

```
clear;clc
A =input('The the judgment matrix is: ');
RI=[0 0 0.52 0.89 1.12 1.26 1.36 1.41 1.46 1.49 1.52 1.54 1.56 1.58 1.59];

%Arithmetic mean method
sumofA = sum(A);
%1: Normalize the judgment matrix as columns
[n,n] = size(A);
SUMofA = repmat(sumofA,n,1);
st_A = A ./ SUMofA;
sum(st_A,2);
%2: Add the normalized columns
disp('The weight obtained by arithmetic mean method is as follows:');
disp(sum(st_A,2) / n)
%3: Divide each element of the vector you add up by n to get the weight vector

%Geometric mean method
product_A = prod(A,2);
%1: Multiply the elements of A by rows to get A new column vector
product_A_n = product_A .^ (1/n);
%2: Each component of the vector power 1/n
disp('The weight obtained by geometric mean method is as follows:');
disp(product_A_n ./ sum(product_A_n));
%3:Normalize to get the weight vector

%Eigenvalue method
[v,d] = eig(A);
%v eigenvector,D is a diagonal matrix composed of eigenvalues
max_eigenvalue = max(d(:))
%1: Find the maximum eigenvalue of matrix A and its corresponding eigenvector
d == max_eigenvalue;
[r,c] = find(d == max_eigenvalue , 1);
v(:,c);
disp('The weight obtained by the eigenvalue method is as follows: ');
disp( v(:,c) ./ sum(v(:,c)) )
% 2: Normalize the eigenvectors to get our weights

%calculate the CR
CI = (max_eigenvalue - n) / (n-1);
CR=CI/RI(n);
disp('CR=');disp(CR);
if CR<0.10
    disp('CR < 0.10, accept');
```

```
else
    disp('CR >= 0.10, judgment matrix is wrong');
end
```

Hmatrix.m

```
clc,clear
data = xlsread('hmatrix.xlsx');
result = zeros(11,11);
for i = 1:369
    x=data(i,1);
    y=data(i,2);
    result(x,y) = result(x,y)+1;
end
disp(result);
B=sum(sum(result))
position = xlsread('position.xlsx');
figure(1);
box on
axis([0,100,0,100]);
grid;

for i=1:11
    x=position(i,1);
    y=position(i,2);
    plot(x,y,'o','markersize',20);
    hold on;
end
hold on;
plot(100,50,'o');
text(87,50,'对方球门');
plot(0,50,'o');
text(3,50,'我方球门');
plot(0,100,'o');
plot(0,0,'o');
plot(100,100,'o');
plot(100,0,'o');
text(3,97,'corner');
text(3,3,'corner');
text(90,3,'corner');
text(90,97,'corner');

text(position(1,1)+2,position(1,2)+2,'G');
text(position(2,1)+2,position(2,2)+2,'D1');
```

```
text(position(3,1)+2,position(3,2)+2,'D2');
text(position(4,1)+2,position(4,2)+2,'D3');
text(position(5,1)+2,position(5,2)+2,'D4');
text(position(6,1)+2,position(6,2)+2,'M1');
text(position(7,1)+2,position(7,2)+2,'M2');
text(position(8,1)+2,position(8,2)+2,'M3');
text(position(9,1)+2,position(9,2)+2,'F1');
text(position(10,1)+2,position(10,2)+2,'F2');
text(position(11,1)+2,position(11,2)+2,'F3');

for i=1:1:11
    for j=1:1:11
        t=result(i,j);
        x1=position(i,1);
        y1=position(i,2);
        x2=position(j,1);
        y2=position(j,2);

        if t>0
            for k=1:t
            plot([x1,x2],[y1,y2],'->','linewidth',min(t,10));
            hold on;
            end
        end

    end
end
```

opmatrix.m

```
clc,clear
data = xlsread('opmatrix.xlsx');
result = zeros(11,11);

for i = 1:197
    x=data(i,1);
    y=data(i,2);
    result(x,y) = result(x,y)+1;
end

 disp(result);
B=sum(sum(result))

position = xlsread('oppoposition.xlsx');
figure(1);
```

```
box on
axis([0,100,0,100]);
grid;

for i=1:11
    x=position(i,1);
    y=position(i,2);
    plot(x,y,'o','markersize',20);
    hold on;
end
hold on;
plot(100,50,'o');
text(87,50,'对方球门');
plot(0,50,'o');
text(3,50,'我方球门');
plot(0,100,'o');
plot(0,0,'o');
plot(100,100,'o');
plot(100,0,'o');
text(3,97,'corner');
text(3,3,'corner');
text(90,3,'corner');
text(90,97,'corner');

text(position(1,1)+2,position(1,2)+2,'G');
text(position(2,1)+2,position(2,2)+2,'D1');
text(position(3,1)+2,position(3,2)+2,'D2');
text(position(4,1)+2,position(4,2)+2,'D3');
text(position(5,1)+2,position(5,2)+2,'D4');
text(position(6,1)+2,position(6,2)+2,'M1');
text(position(7,1)+2,position(7,2)+2,'M2');
text(position(8,1)+2,position(8,2)+2,'M3');
text(position(9,1)+2,position(9,2)+2,'F1');
text(position(10,1)+2,position(10,2)+2,'F2');
text(position(11,1)+2,position(11,2)+2,'F3');

for i=1:1:11
    for j=1:1:11
        t=result(i,j);
        x1=position(i,1);
        y1=position(i,2);
        x2=position(j,1);
        y2=position(j,2);

```

```
        if t>0
            for k=1:t
            plot([x1,x2],[y1,y2],'->','linewidth',min(t,10));
            hold on;
            end
        end

    end
end
```