

# Analyzing Player Involvement in the Indian Pro Kabaddi League: A Network Analysis Approach

Arjab Sengupta<sup>1</sup>[0009-0004-0641-6135], Subhadip Layek<sup>2</sup>[0009-0005-7004-7618] and Krishanu Deyasi<sup>3</sup>[0000-0002-0455-4495]

<sup>1</sup> Department of Electronics and Communication Engineering

<sup>2</sup> Department of Electrical and Electronics Engineering

<sup>3</sup> Department of Basic Science and Humanities

Institute of Engineering & Management, Management House, D-1, Sector-V, Salt Lake Electronics Complex, Kolkata 700091, West Bengal, India  
University of Engineering & Management, New Town, University Area, Plot No. III, B/5, New Town Rd, Action Area III, Newtown, Kolkata 700160, West Bengal, India

krishanu.deyasi@iem.edu.in

**Abstract.** This paper aims to apply network analysis to all players who have participated in the Indian Pro Kabaddi League since its inception. The Kabaddi network has been constructed based on the number of teams and players they have played with. The players have been ranked with the help of the degree and PageRank algorithm. Small-world phenomenon is observed in the Kabaddi network. The significance of the player's performance has been compared with the player's rank received by the network analysis.

**Keywords:** Social network, Kabaddi network, Degree, Clustering coefficient, Average shortest distance, PageRank.

## 1 Introduction

Social networks have become a fundamental paradigm for understanding the complexities of human interactions and relationships in various contexts [1, 2, 3]. With the advent of digital technologies and the proliferation of online platforms, studying social networks has gained significant attention across disciplines such as sociology, communication, and computer science [4, 5].

At its core, a social network comprises individuals or entities (nodes) interconnected by relationships or interactions (edges), forming a complex web of connections. These connections can manifest in diverse forms, including friendship network [6], coauthorship network [7], movie actor network [3], and communication network [8], sports network [9].

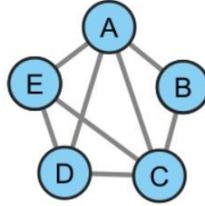
Network science tools have been applied in different sports to analyze the structure of the network. Peña, J.L. *et al.* [10] used network theory to identify play patterns, potential weaknesses, and hotspots of the play using the passing data of the 2010 FIFA World



<b>Telugu Titans</b>	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
<b>Bengaluru Bulls</b>	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
<b>Gujarat Giants</b>					Y	Y	Y	Y	Y	Y

**Table 1:** Here are all the 12 teams in the Pro Kabaddi League and their participation in the last 10 seasons.

Two Kabaddi players are assumed to be connected by an edge if they are part of the same squad in the same season. For example, if players A, B, and C played together on a team in one season, and in another season players A, C, D and E were teammates, then graphically they are represented by Figure 1.



**Figure 1:** Sample network with 5 players. In one season, players A, B, and C were on the same team, while in another season, players A, C, D and E were on the same team.

The constructed network has 863 nodes and 17195 edges. This means that, on average, each player has played around 19 other players in their PKL career. We found that all nodes of the network is in a single giant component [see Figure 2]. This signifies that all the players are connected. In the next section, *degree*, *clustering coefficient* and *average shortest distance* have been calculated. The clustering coefficient and average shortest distance of the Kabaddi network have been compared with the two model networks, *viz.*, Erdős–Rényi (ER) network [17] and the configuration network [18]. PageRank analysis has also been conducted to rank the players.

**2.1 Degree:** Degree of a node  $i$  in a network is defined as [2]:

$$d_i = \sum_{j=1}^N A_{ij}, \quad (1)$$

where  $A$  is called the adjacency matrix defined as  $A_{ij} = 1$  if the players  $i$  and  $j$  are in the same squad and  $A_{ij} = 0$  if the players  $i$  and  $j$  are in the different squads,  $N$  is the total number of players in the network.

From our analysis, PO Surjeet Singh stands out as the player with the highest degree. He has played with 159 players. The top 40 players with the highest degrees are listed in Table 2.

Degree Rank	Player name	Degree ( $d_i$ )
1	PO SURJEET SINGH	159

2	GIRISH MARUTI ERNAK	154
3	K PRAPANJAN	151
4	RAKESH NARWAL	144
5	RAVI KUMAR	144
6	RAHUL CHAUDHARI	143
7	PRASHANTH KUMAR RAI	143
8	ASISH KUMAR SANGWAN	138
9	CHANDRAN RANJIT	138
10	RAVINDER PAHAL	137
11	SELVAMANI K	136
12	DEEPAK NIWAS HOODA	134
13	FAZEL ATRACHALI	131
14	VIJIN THANGADURAI	131
15	SANDEEP NARWAL	130
16	ANIL KUMAR	126
17	PAWAM KUMAR SEHRAWAT	125
18	AMIT HOODA	125
19	PARDEEP NARWAL	125
20	SHRIKANT JADHAV	123
21	VISHAL PRABHAKAR MANE	122
22	SUKESH HEGDE	121
23	AJAY THAKUR	118
24	RAN SINGH	118
25	NITIN TOMAR	117
26	DHARMARAJ CHERALATHAN	116
27	DEEPAK NARWAL	116
28	SURENDER NADA	116
29	VIKAS KANDOLA	115
30	MOHIT CHHILLAR	115

31	HADI OSHTORAK	115
32	MANJEET CHHILLAR	114
33	MAHENDRA GANESH RAJPUT	113
34	SANDEEP DHULL	111
35	VISHAL BHARADWAJ	111
36	PAWAN KUMAR KADIYAN	110
37	PARVESH BHAINSWAL	110
38	RAJESH NARWAL	109
39	C ARUN	109
40	MONU GOYAT	108

**Table 2:** Top 40 highly connected players in the Kabaddi network.

**2.2 Clustering coefficient:** The clustering coefficient ( $C_i$ ) of a node  $i$  is defined as the ratio of the number of edges shared by its neighboring nodes to the maximum number of possible edges among them [2]. Hence, the average clustering coefficient of a network is defined as:

$$C = \frac{1}{N} \sum_{i=1}^N C_i \quad (2)$$

We have got the clustering coefficient of the Kabaddi network to be 0.7280 signifying that the Kabaddi network is highly clustered. The ER network on the other hand has a clustering coefficient of about 0.0462, *i.e.*, in an order that is lower in magnitude than the Kabaddi network. The configuration network has been generated from the original network by keeping the same number of nodes and the same degree sequence as that of the original network. The clustering coefficient of the configuration network is 0.0927, much less than the Kabaddi network but higher than the ER network.

**2.3 Average shortest distance:** The average shortest distance  $l$  between any two vertices is defined as [2]:

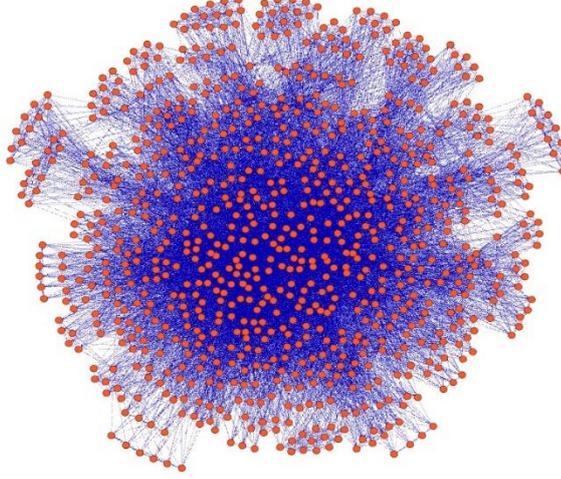
$$l = \frac{2}{N(N-1)} \sum_{i,j \in V} d(i,j) \quad (3)$$

where  $d(i, j)$  denotes the minimum number of edges required to reach from vertex  $i$  to  $j$  and  $V$  is the set of vertices.

The average shortest path distance of the Kabaddi network is 2.349. The high clustering coefficient ( $C$ ) and short average distance ( $l$ ) indicate that the Kabaddi network is a small world network [3]. Compared to the Kabaddi network, the average shortest distance of the ER and configuration networks are 2.105 and 2.187, respectively.

Network	Number of nodes (N)	Number of edges (E)	Average clustering coefficient (C)	Average shortest distance (l)
Kabaddi network (PKL)	863	17195	0.7280	2.349
Erdős–Rényi model	863	17195	0.0462	2.105
Configuration model	863	17195	0.0927	2.187

**Table 2:** Network statistics of the Kabaddi network and the corresponding Erdős–Rényi model [17] and configuration model [18].



**Figure 2:** Network structure of players in the Pro Kabaddi League.

### 3 PageRank analysis

In this section, players have been sorted out in descending order based on the PageRank score of a particular node. PageRank was originally developed by Sergey Brin and Larry Page in 1998 [19]. PageRank is used to rank web pages to deliver search results relevant to user queries. The web pages are considered as nodes and the corresponding hyperlinks which lead to that particular page are considered as edges. The PageRank for an undirected network is defined as [4]:

$$Rank(u_i) = \frac{1-c}{N} + c \sum_{j=1}^N A_{ij} \frac{Rank(u_j)}{k_j} \quad (4)$$

Here,  $c$  is the damping factor/jump factor. Typically, the value of  $c$  is set to 0.85.  $Rank(u_i)$  and  $Rank(u_j)$  are the PageRank scores of the vertices  $i$  and  $j$ , respectively.  $A_{ij}$  is the  $ij$ th element of the adjacency matrix  $A$ .  $k_j$  is the degree of the vertex  $j$ .

In the PageRank analysis, Girish Maruti Ernak emerges as the top-ranked player in the network. Table 3 presents the top 40 players from all 10 seasons of the Pro Kabaddi League as determined by the PageRank analysis.

We have taken the average strike rates of the individual player from [16] and compared them with the PageRank scores of a particular player/node. The average strike rate of a player quantifies the performance of a player over the years. Based on the PageRank score, the top 40 players have been grouped together depending on their assigned scores in Table 3. PageRank score and average strike rate of the top 40 players is negatively correlated with the correlation coefficient value -0.5684. A higher PageRank score indicates a greater number of edges, and therefore, a higher degree [20]. This means that the particular player has played with a relatively larger number of teams compared to the rest of the players. This suggests that the particular player has been released by the franchise or team before the auction of a particular season, indicating that the player's performance within the team may not have been satisfactory for retention. Naturally, we observe an inverse relationship between the overall strike rates of the players and their PageRank scores.

Rank	Name	PageRank Score	Avg Strike Rate (%)
1	GIRISH MARUTI ERNAK	0.003996	45.12
2	K PRAPANJAN	0.003991	42.21
3	PO SURJEET SINGH	0.003959	51.96
4	RAHUL CHAUDHARI	0.003778	45.84
5	RAKESH NARWAL	0.003700	54.31
6	RAVI KUMAR	0.003608	52.98
7	SELVAMANI K	0.003586	46.80
8	ASISH KUMAR SANGWAN	0.003584	48.44
9	CHANDRAN RANJIT	0.003566	40.29
10	PRASHANTH KUMAR RAI	0.003537	49.90
11	RAVINDER PAHAL	0.003497	51.07
12	PAWAN KUMAR SEHRAWAT	0.003384	66.52
13	FAZEL ATRACHALI	0.003361	52.79
14	SANDEEP NARWAL	0.003331	39.65
15	DEEPAK NIWAS HOODA	0.003316	48.02
16	VIJIN THANGADURAI	0.003291	44.92

17	ANIL KUMAR	0.003241	57.36
18	AMIT HOODA	0.003204	53.81
19	PARDEEP NARWAL	0.003190	54.34
20	SHRIKANT JADHAV	0.003170	47.80
21	VISHAL PRABHAKAR MANE	0.003102	52.72
22	SUKESH HEGDE	0.003006	44.84
23	NITIN TOMAR	0.002992	50.13
24	AJAY THAKUR	0.002992	45.95
25	VISHAL BHARADWAJ	0.002980	57.39
26	RAN SINGH	0.002970	49.50
27	SANDEEP DHULL	0.002956	52.25
28	DHARMARAJ CHARALATHAN	0.002935	54.98
29	MAHENDRA GANESH RAJPUT	0.002919	47.43
30	VIKAS KANDOLA	0.002917	48.88
31	DEEPAK NARWAL	0.002915	45.63
32	SURENDER NADA	0.002896	45.22
33	MANJEET CHHILLAR	0.002893	53.63
34	PARVESH BHAINSWAL	0.002886	60.01
35	MOHIT CHHILLAR	0.002874	47.27
36	SANTHAPANASELVAM	0.002873	55.40
37	SOMBIR	0.002872	55.97
38	HADI OSHTORAK	0.002864	55.90
39	C ARUN	0.002819	53.31
40	SHRIKANT TEWTHIA	0.002797	51.37

**Table 3:** Top 40 high PageRank players in the Kabaddi network.

#### 4 Discussion and conclusion

In this paper, we have constructed the Kabaddi network based on the participation of players in the Pro Kabaddi League. We have examined the Kabaddi network as a simple graph, with players as nodes, and an edge connecting two nodes if those players

have been on the same team. Our analysis reveals that the graph has 863 nodes and 17195 edges. It has been observed that the Kabaddi network is highly clustered with the clustering coefficient of 0.7280 and the average shortest path length  $l$  which comes out to be 2.349. Consequently, the network possesses small-world properties. The average degree of the constructed network is 39.83. Finally, we determine the PageRank score of the network. The top 40 players, based on their PageRank scores, unsurprisingly display an inverse relationship with their average strike rates. In some cases, the strike rates of the players tended to drop amongst players who have played the same number of matches. The reason is the players' underperformance, leading to multiple releases from their teams. Consequently, they have played with more teammates, increasing their degrees. In some cases, higher strike rates accompanying higher PageRank scores can be attributed to players consistently performing well. Teams show interest in recruiting these players for future seasons, offering them more money, leading to players switching teams.

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