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HOW TEAM SPORTS BEHAVE AS A TEAM? GENERAL NETWORK METRICS APPLIED TO SPORTS ANALYSIS

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Abstract
The aim of this study was to analyse the general properties of networks in different team sports. Therefore, the analysis of variance to the general network properties between different team sports and different competitive levels was carried out. Sixty-six official matches (from Handball, Basketball, Football, Futsal, Rink-Hockey and Volleyball) were observed in five possible competitive levels (U12, U14, U16, U18 and Amateurs with more than 20 years). Analysis of variance revealed that the type of sport (p = 0.001; η_p^2= 0.647; moderate effect size) and competitive level(p = 0.001; η_p^2= 0.355; small effect size)had significant statistical differences in the general network metrics. It was also found that football generates more connections between teammates but basketball and volleyball promote better results of density and clustering coefficient.

Key words: *Graph Theory; Adjacency Matrices; Network Analysis; Performance; Team Sports*

Introduction

The dynamics on team sports it is evidence from the multiple cooperation-opposition processes that occurs in the match (Gréhaigne, Godbout, & Bouthier, 1999). For that reason, the organization between teammates it is crucial to improve the possibilities to win and increase the collective performance (Bourbousson, Poizat, Saury, & Seve, 2010). Therefore, the regular assumption that the whole it is necessarily different from the total of the parts assumes a great importance in the team sports context (Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012).In fact, the team depends from a set of inter-relationships and spatio-temporal coordination tendencies to achieve the high collective performance(Lusher, Robins, & Kremer, 2010). Thus, the cooperation and the network that emerges from the team it is one of the main key elements to analyse and understand in a team(Duarte, Araújo, Correia, & Davids, 2012; Travassos, Davids, Araújo, & Esteves, 2013). In the specific case of team sports, the social network analysis (SNA) has been recently used to identify the properties of the teams and to understand how success is associated with collective performance(Clemente, Couceiro, Martins, & Mendes, 2015; Clemente, Martins, Kalamaras, Wong, & Mendes, 2015; Grund, 2012). In a study carried out in English Premier League it was considered 283,529 passes between teammates during attacking moments to analyse how network properties are associated with team's performance in football (Grund, 2012). The main findings showed that goals scored were associated with density and centralization metrics, thus suggesting that high levels of co-relationships lead to increased team performance.

By other hand, the authors suggested that a centralized tendency in a team lead with a decrease in team performance (Grund, 2012). In the case of a football team with tendencies to play in quick transitions and counter-attack, it was observed small values of density and great values of centralization suggesting that this style of play centralizes the cooperation in some players (Clemente, Couceiro, et al., 2015). It was also found that clustering coefficient and density are lower in 2nd half of the match (Clemente, Couceiro, et al., 2015). Such evidence it was also showed by the study conducted in football teams during FIFA World Cup 2010 (Cotta, Mora, Merelo, & Merelo-Molina, 2013). This kind of results can be justified by the more unstructured game in 2nd half and by the great space to exploit the counter-attack. Finally, in a recent study conducted during the 64 matches of the FIFA World Cup 2014, it was found that high levels of goals scored were associated with high levels of total links, network density and clustering coefficient (Clemente, Martins, et al., 2015). The analysis of variance it also showed statistical difference in network properties between the teams that achieved Finals and the teams that lose during Round of 16. The greater values of total links, density and clustering coefficient were found in the teams that achieved the final of the competition (Clemente, Martins, et al., 2015). As possible to observe, the collective organization and the tendencies to teammates behave as a whole may be associated with best performances in team sports. Despite of this knowledge, no more studies were made to identify how variances occur from team sport to team sport. In fact, the studies reported are only in football.

Moreover, the studies reported are always about elite teams. Therefore, there a lack in the literature to know how general network properties varies from team sport-to-team sport in different competitive levels. For these reasons, this study aimed to analyse the variance of general network properties between different team sports (Handball, Basketball, Football, Futsal, Rink-Hockey and Volleyball) and competitive levels (U12, U14, U16, U18 and Amateurs with more than 20 years).

Methods

Sample

Sixty-six official matches (from Handball, Basketball, Football, Futsal, Rink-Hockey and Volleyball) were observed in five possible competitive levels (U12, U14, U16, U18 and Amateurs with more than 20 years). Three official matches it were analysed per each competitive level. A total of 23,216 passes were analyzed during the network analysis. This study accomplished the ethical standard for the study in humans based on Declaration of Helsinki.

Procedures and Data Collecting

Only the passes (interactions) during the attacking moments were analysed in this study. Per each passing sequence without interception or lose the ball (unit of attack) it was generated an adjacency matrix. This adjacency matrix represents the direction and the weights between teammates interactions (Clemente, Couceiro, et al., 2015; Passos et al., 2011). In the end of each match, the sum of adjacency matrix it was computed resulted in the final matrix from the game. To codify the teammates' interactions it was attributed a code to each tactical position.

Therefore, each player was assumed as a tactical position that depends from the tactical line up of the team. This procedure it was executed following previous studies in network analysis applied to team sports (Clemente, Martins, et al., 2015; Malta & Travassos, 2014). When a player was replaced by another, a new number was given in accordance with the tactical criteria(Clemente, Martins, et al., 2015). The data collecting and treatment it was made by the same observer. A test-retest analysis it was conducted to guarantee the reliability standards for the studies based on observation. A sample of 10% of the data it was analysed with a 15-day interval and the results were compared using the Cohen's Kappa test (Robinson & O'Donoghue, 2007). A Kappa value of 0.82 was obtained, thus ensuring the recommended margin to this kind of procedures (Robinson & O'Donoghue, 2007).

Network Analysis

The final adjacency matrices from the 66 official matches it were imported and then treated in the Social Networks Visualizer (version 1.8.). This software it allows to compute a set of general and centralization network metrics (Kalamaras, 2014).

From the possible general network metrics, only three were selected based on previous studies (Clemente, Martins, et al., 2015; Cotta et al., 2013; Grund, 2012): i) total arcs; ii) density; and iii) clustering coefficient. Following, each metric will be presented.

Total Arcs

The sum of the elements of each row of the adjacency matrix $\sum_{\substack{i=1 \\ j\neq i}}^{n} a_{ij}, j = 1, \ldots, n$ was the total number of passes from player i to all its other teammates. The sum of all elements $a_{ij}(i \neq j)$ of the adjacency matrix, $L_D^w = \sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}$, is the *total arcs* (passes) between each team's players. In the corresponding weighted directed graph, this number is the total arcsbetween all nodes.

Graph Density

In graph theory, the density of a (directed) graph is the proportion of the maximum possible lines (or arcs) that are present between nodes.In the case of ordered relations, as in the teammate interactions, the possible distinct directed links in a digraph of *n* nodes is $n(n-1)$so the density is computed by:

$$\Delta = \frac{L_D^w}{n(n-1)}. \tag{1}$$

In this case the density is a ratio having a minimum of zero (no arcs present) and a maximum of 1 (all arcs are present).

Clustering Coefficient

The local Clustering Coefficient (CCoefficient) measures the degree of interconnectivity in the neighborhood of a node. The higher it is, the closer this node and its neighbors are to become a clique. The local clustering coefficients(Rubinov & Sporns, 2010) can be computed as follows:

$$\overline{C} = \frac{1}{n}\sum_{i=1}^{n} C_i. \tag{3}$$

where$n = |V|$ is the number of vertices and we consider of C_i based on the type of graph that will be performed (undirected, directed and weighted).

Statistical procedures

The influences of Team Sports and Competitive Level factors on the Total Arcs, Density and CCoefficientwere analyzed using two-way MANOVA after validating normality and homogeneity assumptions. The assumption of normality for each univariate dependent variable was examined using Kolmogorov-Smirnov tests. The assumption of the homogeneity of each group's variance/covariance matrix was examined with the Box's M Test. When the MANOVA detected significant statistical differences between the two factors, we proceeded to the two-way ANOVA for each dependent variable, followed by Tukey's HSD post-hoc test(O'Donoghue, 2012). When the two-way ANOVA showed an interaction between factors, it also generated a new variable that crossed the two factors (e.g., Handball*U12; Handball*U14) for each dependent variable to identify statistical significance(Maroco, 2012).

Ultimately, the statistical procedures used were one-way ANOVA and Tukey HSD post-hoc. If no interactions were detected in two-away ANOVA, a one-way ANOVA was used for each independent variable. All statistical analyses were performed using IBM SPSS Statistics (version 21) at a significance level of$p<0.05$.The following scale was used to classify the effect size(partial eta square) (Lakens, 2013): small, 0.2-0.49; moderate, 0.50–0.79; large, 0.80–1. The relationship between number of players per sport and network metrics (total arcs, densityand clustering coefficient) was investigated using Pearson productmoment correlation coefficient. Preliminary analysis was performed to ensure no violation of the assumptions of normality, linearity, and homoscedasticity, as suggested by Pallant(Pallant, 2011). The following scaleswere used to classify the correlation strength (Hopkins et al., 1996): very small, 0–0.1; small, 0.1–0.3; moderate, 0.3–0.5; large, 0.5–0.7; very large, 0.7–0.9; 0.9–1, nearly perfect; 1, perfect.

Results

Table 1. Descriptive table (mean and standard deviation) and statistical comparison between crossing factors for Total Arcs.

	U12	U14	U16	U18	Amateurs (> 20)
Handball					
TotalArcs	-	34.00 (3.00)	34.67 (1.53)	-	-
Basketball					
TotalArcs	-	19.33 (1.15)	20.00 (0.00)	20.00 (0.00)	20.00 (0.00)
Football					
TotalArcs	34.33 (2.52)	84.33 (7.23)	88.33 (7.64)	79.00 (3.46)	84.67 (7.64)
Rink-Hockey					
TotalArcs	14.67 (1.53)	13.33 (1.53)	14.33 (1.53)	12.67 (0.58)	14.00 (1.00)
Volleyball					
TotalArcs	26.67 (4.16)	-	-	-	26.67 (2.08)
Futsal					
TotalArcs	17.67 (0.58)	16.67 (1.53)	18.67 (1.53)	-	19.33 (0.58)

Table 2. One-way ANOVA values in Team Sport in Competitive Level position in Density.

		M(SD)	F	*p*	η_p^2
U12	Football	0.82 (0.06)	2.082	0.181	0.438
	Rink-Hockey	0.73 (0.08)			
	Volleyball	0.87 (0.14)			
	Futsal	**0.88 (0.03)**			
U14	Football	0.77 (0.07)	7.321	0.005	0.745
	Rink-hockey	0.67 (0.08)[e]			
	Futsal	0.83 (0.08)			
	Handball	0.81 (0.07)			
	Basketball	**0.97 (0.06)**[b]			
U16	Football	0.80 (0.07)[e]	10.766	0.001	0.812
	Rink-Hockey	0.72 (0.08)[e]			
	Futsal	0.93 (0.08)b			
	Handball	0.82 (0.04)[e]			
	Basketball	**1.00 (0.00)**[a,b,f]			
U18	Football	0.72 (0.03)[b,e]	162.557	0.001	0.982
	Rink-Hockey	0.63 (0.03)[a,e]			
	Basketball	**1.00 (0.00)**[a,b]			
Amateurs	Football	0.77 (0.07)[d,e]	17.868	0.001	0.877
	Rink-Hockey	0.70 (0.05)[c,d,e]			
	Volleyball	0.89 (0.07)[b]			
	Futsal	0.97 (0.03)[a,b]			
	Basketball	**1.00 (0.00)**[a,b]			

(Statistical different from Football[a]; Rink-Hockey[b]; Volleyball[c]; Futsal[d]; Basketball[e]; and Handball[f] for a p-value < 0.05)

The two-way MANOVA revealed that the type of sport (p = 0.001; η_p^2= 0.647; *moderate effect size*) andcompetitive level(p = 0.001; η_p^2= 0.355; *small effect size*)had significant statistical differences in the general network metrics.

There was also a significant interaction (Pillai's Trace = 1.263; F = 2.667;p = 0.001; η_p^2= 0.421; *small effect size*) between type of sport and competitive level on general network metrics.

As previously indicated in the statistical procedures, a two-way ANOVA was conducted for each dependent variableafter the confirmation of the interaction (O'Donoghue, 2012, p. 243).Interaction was found between factors for Total Arcs (F = 34.441; p = 0.001; η_p^2= 0.904; *large effect size*). No differences were found between factors for Density (F= 0.677; p = 0.764; η_p^2= 0.156; *small effect size*) and CCoeficient(F= 0.789; p = 0.659; η_p^2= 0.177; *small effect size*).

Table 3. One-way ANOVA values in Competitive Level in each Team Sport in Density.

		M(SD)	F	*p*	η_p^2
Handball	U14	0.81 (0.07)	0.136	0.731	0.033
	U16	**0.83 (0.04)**			
Basketball	U14	0.97 (0.06)	1.000	0.441	0.273
	U16	1.00 (0.00)			
	U18	1.00 (0.00)			
	Amateurs	**1.00 (0.00)**			
Football	U12	**0.82 (0.06)**	1.123	0.399	0.310
	U14	0.77 (0.07)			
	U16	**0.80 (0.07)**			
	U18	0.72 (0.03)			
	Amateurs	0.77 (0.07)			
Rink-Hockey	U12	**0.73 (0.08)**	1.160	0.384	0.317
	U14	0.67 (0.08)			
	U16	0.72 (0.08)			
	U18	0.63 (0.03)			
	Amateurs	0.70 (0.05)			
Volleyball	U12	0.89 (0.07)	0.001	0.973	0.001
	Amateurs	**0.89 (0.07)**			
Futsal	U12	0.88 (0.03)	3.062	0.091	0.535
	U14	0.83 (0.08)			
	U16	0.93 (0.08)			
	Amateurs	**0.97 (0.03)**			

(Statistical different from Handball[a]; Basketball[b]; Football[c]; Rink-Hockey[d]; Volleyball[e]; and Futsal[f] for a p-value < 0.05)

Table 4. One-way ANOVA values in Team Sport in Competitive Level position in CCoefficient.

		M(SD)	F	*p*	η_p^2
U12	Football	0.84 (0.08)	0.454	0.722	0.146
	Rink-Hockey	0.80 (0.00)			
	Volleyball	**0.90 (0.13)**			
	Futsal	0.85 (0.14)			
U14	Football	0.82 (0.05)	2.802	0.850	0.528
	Rink-hockey	0.80 (0.00)			
	Futsal	0.83 (0.09)			
	Handball	0.82 (0.10)			
	Basketball	**0.97 (0.06)**			
U16	Football	0.88 (0.04)	4.328	0.027	0.634
	Rink-Hockey	0.80 (0.00)[e]			
	Futsal	0.90 (0.13)			
	Handball	0.85 (0.02)			
	Basketball	**1.00 (0.00)[b]**			
U18	Football	0.75 (0.07)[e]	31.324	0.001	0.913
	Rink-Hockey	0.80 (0.00)[e]			
	Basketball	**1.00 (0.00)[a,b]**			
Amateurs	Football	0.81 (0.07)[d,e]	9.664	0.002	0.794
	Rink-Hockey	0.80 (0.00)[d,e]			
	Volleyball	0.90 (0.08)			
	Futsal	0.97 (0.03)[a,b]			
	Basketball	**1.00 (0.00)[a,b]**			

(Statistical different from Football[a]; Rink-Hockey[b]; Volleyball[c]; Futsal[d]; Basketball[e]; and Handball[f] for a p-value < 0.05)

The one-way ANOVA tested the crossing between factors for Total Arcs revealed statistical differences (F = 186.895; *p* = 0.001; η_p^2= 0.989; *large effect size*), The post-hoc results observed are shown in Table 1.One-way ANOVA was used as no interaction between factors was found. The results for Density (Table 2) showed statistical differences in the U14 (F = 7.32; *p* = 0.00; η_p^2 = 0.75; *moderate effect size*), U16 (F = 10.77; *p* = 0.00; η_p^2 = 0.81; *large effect size*), U18 (F = 162.56; *p* = 0.00; η_p^2 = 0.98; *large effect size*) and Amateurs (F = 17.87; *p* = 0.00; η_p^2 = 0.88; *large effect size*). No statistical differences were found in U12 (F = 2.082; *p* = 0.18; η_p^2 = 0.44; *small effect size*). One-way ANOVA was used as no interaction between factors was found.

The results for Density (Table 3) showed no statistical differences in the handball (F = 0.14; *p* = 0.73; η_p^2 = 0.03; *small effect size*), basketball (F = 1.00; *p* = 0.44; η_p^2 = 0.27; *small effect size*), football (F = 1.12; *p* = 0.39; η_p^2 = 0.31; *small effect size*), rink-hockey (F = 1.16; *p* = 0.38; η_p^2 = 0.32; *small effect size*), volleyball (F = 0.00; *p* = 0.97; η_p^2 = 0.00; *small effect size*) and futsal (F = 3.06; *p* = 0.09; η_p^2 = 0.54; *moderate effect size*). One-way ANOVA was used as no interaction between factors was found. The results for Density (Table 4) showed statistical differences in the U16 (F = 4.33; *p* = 0.03; η_p^2 = 0.63; *moderate effect size*), U18 (F = 31.32; *p* = 0.00; η_p^2 = 0.91; *large effect size*) and Amateurs (F = 9.66; *p* = 0.00; η_p^2 = 0.79; *moderate effect size*).

Table 5. One-way ANOVA values in Competitive Level in each Team Sport in CCoefficient.

		M(SD)	F	p	η_p^2
Handball	U14	0.82 (0.10)	0.294	0.617	0.068
	U16	**0.85 (0.02)**			
Basketball	U14	0.97 (0.06)	1.000	0.441	0.273
	U16	1.00 (0.00)			
	U18	1.00 (0.00)			
	Amateurs	**1.00 (0.00)**			
Football	U12	0.84 (0.08)	1.536	0.265	0.381
	U14	0.82 (0.05)			
	U16	**0.88 (0.04)**			
	U18	0.75 (0.07)			
	Amateurs	0.81 (0.07)			
Rink-Hockey	U12	0.80 (0.00)	-	1.00	1.00
	U14	0.80 (0.00)			
	U16	0.80 (0.00)			
	U18	0.80 (0.00)			
	Amateurs	**0.80 (0.00)**			
Volleyball	U12	0.90 (0.13)	0.001	0.972	0.001
	Amateurs	**0.90 (0.08)**			
Futsal	U12	0.85 (0.14)	0.985	0.447	0.270
	U14	0.83 (0.09)			
	U16	0.90 (0.13)			
	Amateurs	**0.97 (0.03)**			

(Statistical different from Handball[a]; Basketball[b]; Football[c]; Rink-Hockey[d]; Volleyball[e]; and Futsal[f] for a p-value < 0.05)

Table 6. Correlation values between the number of playersper team sport and the network values provided by the metrics.

	Total Arcs	Density	Clustering Coefficient
Number of Players	0.987**	-0.266*	-0.295*

* Correlation is significant at p ≤ 0.050. ** Correlation is significant at p = 0.001.

No statistical differences were found in U12 (F = 0.45; p = 0.72; η_p^2 = 0.15; *small effect size*) and U14 (F = 2.802; p = 0.85; η_p^2 = 0.53; *moderate effect size*). One-way ANOVA was used as no interaction between factors was found. The results for Density (Table 5) showed no statistical differences in the handball (F = 0.29; p = 0.62; η_p^2 = 0.07; *small effect size*), basketball (F = 1.00; p = 0.44; η_p^2 = 0.27; *small effect size*), football (F = 1.54; p = 0.27; η_p^2 = 0.38; *small effect size*), rink-hockey (F = - ;p = 1.00; η_p^2 = 1.00; *small effect size*), volleyball (F = 0.00; p = 0.97; η_p^2 = 0.00; *small effect size*) and futsal (F = 0.99; p = 0.45; η_p^2 = 0.27; *small effect size*). The relationship between number of players per team sport and network variables was investigated using Pearson product-moment correlation coefficient. The values of the coefficientsare shown in Table 6. The number of players per team sport showed a small negative correlation with density (r = -0.266; p = 0.031) and CCoefficient (r = -0.295; 0.016). A nearly perfect positive correlation between number of players and total arcs it was found (r = 0.987; 0.001).

Discussion

There are differences in network properties between team sports? This was the main research question of this study that compared six team sports. In previous studies it was found that the greater cooperation between teammates can deal with a increase in the collective performance (Grund, 2012).

Nevertheless, no studies have been made so far to analyse the variance level between different team sports. Thus, more than identify if the better values that characterize the performance, there was some relevance in to understand if the cooperation varies based on specific team sports dynamics. In this study it was found that football and handball had the bigger values of total arcs in all competitive levels. Such value must be carefully understood taking in account that football and handball have a greater number of players (11 and 7, respectively) than the remaining team sports. For that reason, the correlation test it was carried out to identify if number of players are correlated with Total Arcs. The value of correlation it was nearly perfect, thus the justification of the players it is due by the number of players. For that reason, it is possible to suggest that the greater have the a team sport, greater will be the possibilities of connections thus leading with a more complex network (Wasserman & Faust, 1994). Besides the hypothesis of possibilities of actions, total arcs it is an absolute algorithm that do not allow relativizing the result to compare with different samples. Based on that fact, maybe in the future this kind of metric must be adjusted to a relative algorithm or even do not use this metric to compare different samples. In other way, two other metrics it were used in this study. These metrics relativize the results, allowing comparing with different standards. In the case of density metric (that varies from 0 to 1, minimum and maximum respectively) it was found differences between team sports in U14, U16, U18 and amateurs competitive levels.

In all these competitive levels the greater values of density it was found in basketball and lowest in rink-hockey. Such results can be associated with the fact that basketball do not use goalkeeper, thus increasing the possibility of participation of all players during attacking moments. By other hand, in the rink hockey sport the action of goalkeeper it is constrained by their equipment being a specific position almost restricted to the task of defence. Thus, sports with goalkeepers reduce the possibility of density levels based on fact that these specific tactical positions have specific missions based on defensive moments. In an alternative point-a-view, the variance of density it was tested between different competitive levels per each team sport. The results found that in the sports of handball, basketball, volleyball and futsal the greater values of density it was found in the older stage (amateurs with more than 20 years old). These results may suggest that in older stages the dynamic of cooperation increases based on a homogenization of the style of play. In younger levels, there are some tendencies to centralize the cooperation in the better players constrained by the maturation or the technical level (Vaeyens, Philippaerts, & Malina, 2005). Only in football (U12) and rink-hockey it were achieved greater values in younger stages. In the case of football it is possible to justify the results by the fact that in U12 the format of play it is 7-a-side what it is different from the regular 11-a-side in the remaining competitive levels. As observed in the correlation test, there are a small negative correlation between density and the number of players what means that smaller formats deal with greater density. By the other hand, it is more complex to explain the results found in rink hockey. Maybe in the future will be useful to use some other tactical variables to explain the results that come from network analysis. Besides the density, the variance of clustering coefficient between team sports per competitive levels it was analysed. Statistical differences between team sports were found in U16, U18 and amateurs with more than 20 years old. Particularly, basketball had the greater values and football and rink-hockey the lowest values of clustering coefficient. These results suggest that in basketball there are a very small tendency to generate small communities inside the team, thus the teammates play together and each attacking unit may involve the majority of the players. In other hand, in football and rink-hockey may have the possibility to generate sub-communities inside the team that emerges from the spatiotemporal relationships based on strategy and tactical missions. In other way, the variance of clustering coefficient between team sports per each competitive level it was analysed. The results did not found statistical differences between competitive levels. There are small a tendency to greater average values in older stages of competition. Nevertheless, this variance it too reduced and may suggest that the intrinsic dynamic of each sport may lead with similar relationships in different competitive levels. This study had some limitations. The total arcs it is an absolute metric witch reduces the possibility to compare team sports with different number of players. Another limitation it was the impossibility to collect data in all competitive levels per team sport. Therefore, in future studies will be necessary to increase the sample of data collection and to adjust the algorithm of total arcs to generalize their application to different team sports. Moreover, in future studies will be important to apply some tactical metrics that improve the possibility to process a relationship between network results and the style of play of a team. This future approach will help to bring new knowledge about the team sports dynamics.

Conclusion

The variance of general network metrics between different team sports and competitive levels it were analysed in this study. It was found that team sports with greater number of players increases the values of total arcs. In other hand, team sports with smaller players increases the density values and the clustering coefficient, thus suggesting the better values of cohesion emerges in smaller formats. In the future will be necessary to readjust some network metrics to allow to compare different samples and will be also important to add some variables based on tactical performance to cross them with network analysis.

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KAKO SE MOMČAD PONAŠA KAO MOMČAD? OPĆA MREŽNA METRIKA PRIMJENJENA NA SPORTSKE ANALIZE

Sažetak
Cilj ovog istraživanja bio je analizirati opće svojstva mreže u različitim momčadskim sportovima. Stoga je provedena analiza varijance s općim mrežnim svojstvima između različitih timskih sportova i različitih natjecateljskih razina. Šezdeset i šest službenih utakmica (od rukometa, košarke, nogometa, malog nogometa, klizalište-hokeja do odbojke) zabilježeno je u pet mogućih razina natjecanja (U12, U14, U16, U18 i amateri s više od 20 godina). Analiza varijance pokazala je da prema vrsti sporta (p = 0,001; η_p ^ 2 = 0,647; umjerena veličina učinka) i natjecateljskoj razini (p = 0,001; η_p ^ 2 = 0,355; mala veličina učinka) postoje značajne statističke razlike u općim mjerenjima mreže. Također je utvrđeno da nogomet generira više veze unutar momčadi ekipe, ali i košarka i odbojka su promovirale bolje rezultate gustoće i koeficijenta klastera.

Ključne riječi: *teorija grafova, susjedne matrice, mrežna analiza, izvedba, momčadski sportovi*

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