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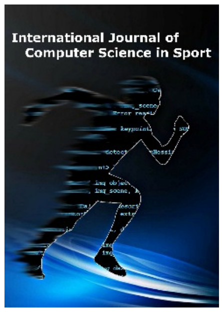

Network structure of UEFA Champions League teams: association with classical notational variables and variance between different levels of success

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Abstract

The aim of this study was to analyse the general properties of the network of elite football teams that participated in UEFA Champions League 2015–2016. Analysis of variance of the general network measures between performances in competition was made. Moreover, the association between performance variables (goals, shots, and percentage of ball possession) and general network measures also was tested. The best sixteen teams that participated in UEFA Champions League 2015–2016 were analysed in a total of 109 official matches. Statistically significant differences between maximum stages in competition were found in total links ($p = 0.003$; $ES = 0.087$), network density ($p = 0.003$; $ES = 0.088$), and clustering coefficient ($p = 0.007$; $ES = 0.078$). Total links ($r = 0.439$; $p = 0.001$), network density ($r = 0.433$; $p = 0.001$) and clustering coefficient ($r = 0.367$; $p = 0.001$) had a moderate positive correlations with percentage of ball possession. This study revealed that teams that achieved the quarterfinals and finals had greater values of general network measures than the remaining teams, thus suggesting that higher values of homogeneity in network process may improve the success of the teams. Moderate correlations were found between ball possession and the general network measures suggesting that teams with more capacity to perform longer passing sequences may involve more players in a more homogeneity manner.

KEYWORDS: APPLIED MATHEMATICS; GRAPH THEORY; SOCCER; FOOTBALL; MATCH ANALYSIS.

Introduction

The organization process and inter-relationships among teammates may define the capacity to be successful or not in team sports (Lago-Ballesteros & Lago-Peñas, 2010). The dynamic of the game and the nature of the cooperation-opposition process are the main challenges to teams and for that reason the observation of network structure may help coaches identify the main weaknesses and strengths of the team and of the opponents (Carling, Williams, & Reilly, 2005; Lago-Ballesteros & Lago-Peñas, 2010).

Classical match analyses are based in notational variables that quantify the actions and behaviours that occur during the match (Hughes and Franks, 2004). The codification and reliability of the data collection are truly important to ensure the quality of interpretation (Hughes and Bartlett, 2002). Variables such as passes, shots, receives, possession of the ball or tactical behaviours are the most common variables collected and analysed in the specific case of football (Sarmento et al., 2014).

Studies using classical notational analysis have found that the most successful teams had more shots on goal, greater efficacy on shots and greater volumes of passes made between teammates (Armatas, Yiannakos, Zaggelidis, Papadopoulou, & Fragkos, 2009; Lago-Ballesteros & Lago-Peñas, 2010). Moreover, situational variables such as home matches also contribute to increase attack indicators such as goals scored, volume of shots, attacking moves, box moves, crosses assists, passes, dribbles and ball possession (Lago-Peñas & Lago-Ballesteros, 2011). The association between variables also reveals that in some competitions long passes and direct style are more strongly associated with a greater volume of goals scored (Hughes and Franks, 2005). Moreover, counterattack may be more effective than indirect play style against unbalanced teams (in defensive organization) (Albin Tenga, Holme, Ronglan, & Bahr, 2010). These evidences contributed to characterize football over the years (Sarmento et al., 2014).

Nevertheless, classical notational analyses are very limited in explaining the causes of the outcomes (Vilar et al., 2013). For that reason, new computational advances and mathematical techniques have been applied in the field of match analysis to characterize a team's dynamics and to analyse behaviours that may justify the final notational outcomes (Travassos et al., 2013; Vilar et al., 2012). Spatiotemporal measures (Bourbousson, Sève, & McGarry, 2010; Duarte, Araújo, Correia, & Davids, 2012), temporal patterns analysis (Jonsson et al., 2006), tactical metrics (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2014), neural network analysis (Memmert & Perl, 2009) and social network analysis (Grund, 2012; Peña & Touchette, 2012) have been suggested in the last decade to complement the quantification of classical notational analysis. Some of these approaches are quite different from the notational analysis (spatiotemporal measures or tactical metrics), while the others are updated versions of notational analysis that use some algorithms to determine some specificities of the team's organization process (Clemente et al., 2014).

One of the more recent techniques that uses regular performance variables (such as passes) to determine some patterns of interactions is the social network analysis based on graph theory (Grund, 2012). This mathematical technique may characterize players as nodes of a graph and the performance variables (such as passes) as the arrows (Passos et al., 2011). General properties of the graph, sub-graphs and centrality measures may be computed based on the adjacency matrices that come from the social network analysis (Wasserman & Faust, 1994).

General measures enable the characterization of the overall structure of a graph (team) (Clemente, Martins, & Mendes, 2016). Network density, total links, homogeneity or clustering coefficients (global) usually are used in the specific field of sports analysis (Clemente, Martins, Kalamaras, Wong, & Mendes, 2015; Grund, 2012). The study conducted by Grund (2012) analysed the network properties of all teams that participated in 760 Premier League soccer matches and associated the network density and homogeneity levels with the performance measured by the volume of goals scored. The study revealed that greater values of network density and homogeneity were associated with the best performances; therefore, teams that have a greater centralization (in specific players) may have a decrease in performance (Grund, 2012). Following a similar analysis, a study that analysed all the matches of the FIFA World Cup 2014 revealed that network density, total links and clustering coefficients had positive correlations with the volume of goals scored (Clemente et al., 2015).

Despite the analyses carried out in the last few years, no study has compared different performance indicators with the general properties of a graph nor has research studied the world-famous UEFA Champions League so far. Based on those reasons, our motivation was to associate different performance variables (passes, shots, goals scored, goals suffered, ball possession, final score) with the general properties of successful teams in the UEFA Champions League 2015–2016. We also performed an analysis of variance to determine the influence of match status and tactical line-up on general properties of a graph. Tactical line-up was considered in this analysis to identify if the formations may influence the network process between teammates, mainly considering that the relationships between teammates can be constrained by the space and the distance.

Methods

Sample

The best sixteen teams that participated in UEFA Champions League 2015–2016 were analysed in a total of 109 official matches. The criteria to define the best teams were classifications for the round of 16 in the competition. All of the matches played by the teams from the group stage until the final match were observed and codified. The network analysis was based on the passing sequences performed by the teams.

Procedures

The observational approach of this study classified players by tactical positions as done previously in similar studies (Clemente et al., 2015). Moreover, each team's tactical line-up was collected and classified. One expert sport analyst made the observation and codification. The reliability of the codification was tested with Cohen's Kappa test with 25% of the full data and 20-day intervals. A kappa value of 0.89 was obtained, thus ensuring a strong value of reliability (Robinson & O'Donoghue, 2007). The following tactical line-ups were codified: i) 1-4-3-3; ii) 1-4-4-2 classical; iii) 1-3-5-2; iv) 1-5-3-2; v) 1-4-4-2 diamond; vi) 1-4-3-2-1; vii) 1-4-2-3-1; viii) 1-4-5-1; ix) 1-3-4-3.

The adjacency matrices of passes were collected from the official website of UEFA Champions League (http://www.uefa.com/uefachampionsleague/). Because we considered the direction and weights of passes, we worked with weighted digraphs (Wasserman & Faust, 1994). The adjacency matrices identified the direction of passes (player A to player B or player B to player A) and the weight of connections (number of passes in the direction).

The classical notational variables of shots to the goal, goals scored, goals suffered and ball possession also were collected from the UEFA Champions League statistical reports.

Network analysis

The adjacency matrices extracted per team and per match were imported into Social Networks Visualizer software (SocNetV, version 1.9). This software enables the user to visualize the graphs and to compute general and centrality network measures (Kalamaras, 2014). Three general network measures were computed: total links, network density and clustering coefficient (average of players).

Total links

Total links measure the total number of connections between teammates (Clemente et al., 2016). A greater value of total links reveals that teammates can be more linked between each other. Given one weighted digraph *G* with n vertices, the total links index, L_D^w, of *G* can be computed as follows (Rubinov & Sporns, 2010)

$$L_D^w = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} a_{ij}, \tag{1}$$

where a_{ij} are elements of the weighted adjacency matrix of a *G*.

Network density

Network density measure the overall affection between teammates by a relative index (Clemente et al., 2016). A greater value suggests a greater overall affection and higher levels of homogeneity among teammates. Given one weighted digraph *G* with *n* vertices. The density index, Δ_D^w, of *G* can be computed as follows (Wasserman & Faust, 1994):

$$\Delta_D^w = \frac{L_D^w}{n(n-1)} \tag{2}$$

where L_D^w is the total links index of a *G*.

Clustering coefficient

This measure calculates the capacity of a player to promote clusters or union in a team. Nevertheless, the average of the team allow identifying the capacity of a team to act together or to generate sub-communities in the team. Consider *G* as weighted digraph with *n* vertices. The clustering coefficient index, $CL_D^w(n_i)$, of a vertex n_i can be calculated as follows (Fagiolo, 2007):

$$CL_D^w(n_i) = \frac{\sum_{j,h} \left(a_{ij}^{\frac{1}{3}} + a_{ji}^{\frac{1}{3}}\right)\left(a_{ih}^{\frac{1}{3}} + a_{hi}^{\frac{1}{3}}\right)\left(a_{jh}^{\frac{1}{3}} + a_{hj}^{\frac{1}{3}}\right)}{2\left[\left(k_i^{out} + k_i^{in}\right)\left(k_i^{out} + k_i^{in} - 1\right) - 2\sum_{j \neq i} a_{ij} a_{ji}\right]},$$

$$= \frac{\left[A^{\left[\frac{1}{3}\right]} + (A^T)^{\left[\frac{1}{3}\right]}\right]_{ii}^{3}}{2\left[\left(k_i^{out} + k_i^{in}\right)\left(k_i^{out} + k_i^{in} - 1\right) - 2\sum_{j \neq i} a_{ij} a_{ji}\right]} \tag{3}$$

where a_{ij} are elements of the weighted adjacency matrix of a G, k_i^{out} is outdegree index of vertex n_i, k_i^{in} is indegree index of vertex n_i and $A^{\left[\frac{1}{3}\right]} = \left[a_{ij}^{\frac{1}{3}}\right]$ (Clemente et al., 2016).

Statistical Procedures

Two-way multivariate analyses of variance (MANOVA) were tested to analyse the variance of general network measures between tactical line-ups and match status. In case of interactions between factors, a two-way analysis of variance (ANOVA) was tested for each dependent variable. Finally, a one-way ANOVA followed by Tukey HSD post-hoc test was carried out to analyse the variance within the factor. Effect size (ES) was tested and interpreted using the following criteria (Ferguson, 2009): no effect (ES < 0.04); minimum effect (0.04 < ES < 0.25); moderate effect (0.25 < ES < 0.64); and strong effect (ES > 0.64).

This study tested the association between classical notational variables of performance (goals scored, goals suffered, shots on goal, ball possession) and the network variables (total links, network density and average clustering coefficient). The association was tested with the Pearson product moment correlation coefficient. The following scale was used to classify the correlation strength (Hopkins, Hopkins, & Glass, 1996): 0.0-0.1 very small; 0.1-0.3 small; 0.3-0.5 moderate; 0.5-0.7 large; 0.7-0.9 very large; 0.9-1 nearly perfect; and 1 perfect.

The statistical procedures were made using the SPSS software (version 23.0, Chicago, Illinois, USA) for a statistical significance of 5%.

Results

Table 1 presents the descriptive statistics of general network measures per team. Bayern Munich, Paris Saint-Germain (PSG) and Barcelona had the highest values of total links (93.08, 91.44 and 90.40, respectively) and network density (0.85, 0.83 and 0.82, respectively). On the other hand, Manchester City, Juventus and Atlético Madrid had the lowest values of total links (67.27, 73.00 and 74.54, respectively) and network density (0.61, 0.66 and 0.68, respectively). PSG had the highest value of clustering coefficient (0.89) and Manchester City had the lowest (0.58).

We used a two-way MANOVA to test the variance of match status (final score) and tactical line-up on the multivariate composite of general network measures. We found no statistically significant differences of network measures between match status (p = 0.94; ES = 0.006, no effect) and tactical line-up (p = 0.43; *ES* = 0.051, minimum effect). Analysis also did not show an interaction between match status and tactical line-up (Pillai's Trace = 0.189; p = 0.621; *ES* = 0.063, minimum effect).

We performed an ANOVA test and a post-hoc test to determine if differences existed between the maximum stage in competition and the network characteristics of teams (Table 2). Statistically significant differences between maximum stage in competition were found in total links (p = 0.003; *ES* = 0.087, minimum effect), network density (p = 0.003; *ES* = 0.088, minimum effect) and clustering coefficient (p = 0.007; *ES* = 0.078, minimum effect). The highest values of total links and network density were found in the teams that only achieved the quarterfinals, followed by the teams that achieved the final.

Table 1. Descriptive statistics (mean, standard deviation and CI %95) of network measures per team.

Teams [Maximum stage on competition]	**Total Links M(SD) [CI95%]**	**Network Density M(SD) [CI95%]**	**Clustering Coefficient M(SD) [CI95%]**
Real Madrid [Finals]	89.54(3.82) [85.51-93.57]	0.81(0.04) [0.78-0.85]	0.85(0.04) [0.81-0.90]
Paris Saint-Germain (PSG) [Quarterfinals]	91.44(4.64) [86.60-96.29]	0.83(0.04) [0.79-0.87]	0.89(0.04) [0.83-0.94]
Philips Sport Vereniging (PSV) [Round of 16]	86.13(8.90) [80.99-91.27]	0.79(0.08) [0.74-0.83]	0.81(0.06) [0.75-0.87]
Wolfsburg [Quarterfinals]	88.70(5.54) [84.10-93.30]	0.81(0.05) [0.77-0.85]	0.83(0.04) [0.78-0.89]
Atlético Madrid [Finals]	74.54(10.79) [70.51-78.57]	0.68(0.10) [0.64-0.72]	0.73(0.14) [0.68-0.78]
Benfica [Quarterfinals]	82.80(7.63) [78.20-87.40]	0.75(0.07) [0.71-0.80]	0.78(0.07) [0.73-0.84]
Juventus [Round of 16]	73.00(11.60) [67.86-78.14]	0.66(0.10) [0.62-0.71]	0.70(0.15) [0.64-0.76]
Manchester City [Semifinals]	67.27(11.77) [62.89-71.66]	0.61(0.11) [0.57-0.65]	0.58(0.19) [0.52-0.63]
Barcelona [Quarterfinals]	90.40(4.12) [85.80-95.00]	0.82(0.04) [0.78-0.86]	0.87(0.02) [0.82-0.93]
Roma [Round of 16]	81.13(9.72) [75.99-86.27]	0.74(0.09) [0.69-0.78]	0.79(0.10) [0.73-0.85]
Bayern Munich [Semifinals]	93.08(2.57) [88.89-97.28]	0.85(0.02) [0.81-0.88]	0.88(0.03) [0.83-0.93]
Arsenal [Round of 16]	82.88(4.05) [77.74-88.02]	0.75(0.04) [0.70-0.79]	0.80(0.08) [0.74-0.87]
Chelsea [Round of 16]	84.38(5.78) [79.24-89.52]	0.77(0.05) [0.72-0.81]	0.82(0.05) [0.76-0.88]
Dynamo Kiev [Round of 16]	81.88(5.39) [76.74-87-02]	0.75(0.05) [0.70-0.79]	0.82(0.04) [0.76-0.88]
Zenit [Round of 16]	81.50(7.95) [76.36-86.64]	0.74(0.07) [0.69-0.79]	0.80(0.09) [0.74-0.87]
Gent [Round of 16]	85.00(2.51) [79.86-90.14]	0.77(0.02) [0.73-0.82]	0.83(0.04) [0.77-0.89]

M: mean; SD: standard deviation; CI95%: Coefficient of interval 95%

Table 2. Descriptive values (mean, standard deviation and CI95%) and statistical comparison between factors (maximum stage reached in UEFA Champions League)

	Round of 16 M(SD) [CI95%]	**Quarter finals** M(SD) [CI95%]	**Semi finals** M(SD) [CI95%]	**Finals** M(SD) [CI95%]
Total Links	81.98(8.08)^{b} [79.59-84.38]	88.48(6.48)^{a,c} [85.45-91.50]	80.96(15.19)^{b} [77.05-84.87]	82.04(11.02) [78.28-85.79]
Network Density	0.74(0.07)^{b} [0.72-0.77]	0.80(0.06)^{a,c} [0.77-0.83]	0.74(0.14)^{b} [0.70-0.77]	0.75(0.10) [0.71-0.78]
Clustering Coefficient	0.80(0.09) [0.77-0.83]	0.84(0.06)^{c} [0.81-0.88]	0.74(0.20)^{b} [0.70-0.79]	0.79(0.12) [0.75-0.84]

Significant different compared with Round of 16^{a}; Quarterfinals^{b}; Semifinals^{c}, and Finals^{d} at $p < 0.05$
M: mean; SD: standard deviation; CI95%: Coefficient of interval 95%

The influence of tactical line-up in the network measures also was tested with a one-way ANOVA. Significant statistical differences were found in total links (p = 0.009; ES = 0.119, minimum effect), network density (p = 0.011; ES = 0.115, minimum effect) and clustering coefficient (p = 0.017; ES = 0.109, minimum effect). The post-hoc test revealed that line-up 1-4-3-3 had statistical greater total links (p = 0.002), network density (p = 0.003) and clustering coefficient (p = 0.007) than the 1-4-4-2 formation.

We also used a one-way ANOVA to test the variance of network measures between different match status. No significant statistical differences were found in total links (p = 0.367; ES = 0.013, no effect), network density (p = 0.363; ES = 0.013, no effect) and clustering coefficient (p = 0.951; ES = 0.001, no effect).

The association between team performance variables (goals scored, goals conceded, shots on goal, shots missed, saves and percentage of ball possession) and the general properties of the network (total links, network density and clustering coefficient) was investigated using the Pearson product-moment correlation coefficient. The values of the coefficient can be observed in Table 3.

Total links (r = 0.439; p = 0.001), network density (r = 0.433; p = 0.001) and clustering coefficient (r = 0.367; p = 0.001) had a moderate positive correlation with the percentage of ball possession.

Discussion

The collective organization of a team depends on the model and style of play. The cooperation that emerges from this model of play can be observed in different points of view. One of the easy-to-observe cooperation processes is the pass between teammates. For that reason, our aim was to analyse the interaction between teammates during attacking building. Social network analysis was used to study this process. We have found that tactical line-up may constrain the structure of the network. The study of association between performance variables and properties of network structure revealed a moderate correlation with the percentage of ball possession.

Table 3. Correlation values between team performance variables and the network measures

	GS	GC	SG	SM	S	%BP
Network Measures						
TL: Total links	0.099	-0.020	0.119	0.069	0.071	0.439*
ND: Network density	0.095	-0.029	0.111	0.070	0.069	0.433*
CC: Clustering coefficient	0.060	-0.049	0.029	0.058	0.043	0.367*

Legend: Goals scored (GS); goals conceded (GC); shots on goal (SG); shots missed (SM); saves (S); percentage of ball possession (%BP). *Correlation is significant at $p < 0.01$

Passes have been analysed regularly by classical notational analysis (M. Hughes & Franks, 2005). Nevertheless, the passing strategies for successful and unsuccessful teams do not differ, suggesting that this variable does not discriminate teams because two teams may have similar volume and frequency of passes (Scoulding, James, & Taylor, 2004). Based on such a methodological constraint, social network analysis recently has been proposed to identify the patterns behind the passes (Duch, Waitzman, & Amaral, 2010; Lusher, Robins, & Kremer, 2010). The study conducted in the English Premier League revealed that teams with the greatest volumes of network density had better performances (goals scored) (Grund, 2012). Similar evidence was found in a study that analysed all the matches from the FIFA World Cup 2014 (Clemente et al., 2015).

In our study, six performance variables were measured (goals scored, goals conceded, shots on goal, shots missed, saves and percentage of ball possession). The results of association revealed a very small correlation between network density and the majority of performance variables (including the goals scored). A positive, moderate and significant correlation was found only with the percentage of ball possession. This is not in line with the English Premier League and FIFA World Cup 2014 studies. The specificity of our study may have constrained the results. All teams were analysed in the above-mentioned competitions but our study focused only on the top sixteen teams from the UEFA Champions League. This may have had some influence in the final outcomes.

The ANOVA of network measures between successful levels in competition (maximum stage in the Champions League) also revealed some interesting and atypical evidence. The comparison between successful levels in competition was first studied in the FIFA World Cup 2014 (Clemente et al., 2015). Progressively greater network densities and total links were observed until the teams achieved the finals.

In our study, the teams that achieved only the quarterfinals (Wolfsburg, Barcelona, Benfica and PSG) achieved greater values of network density and total links, followed by the finalists (Real Madrid and Atlético Madrid). This result may have been influenced by Barcelona and PSG, which were the teams with the greatest values of network density and total links. Barcelona actually represents the football of 'tiki-taka' (Peña & Touchette, 2012) with a high volume of passes among all the teammates (great volume of density). Nevertheless, this may have been an outlier that influenced the results. On the other hand, Atlético Madrid (defeated in the final) is the opposite of 'tiki-taka' (it had one of the lowest values of network density and total links). Both evidences constrained the final results, which therefore are not in line with previous studies of national teams (Clemente et al., 2015). The comparison between succeeded and non-succeeded teams in the competition may not be the most appropriate analysis. The potential of discrimination of network analysis is too small to differentiate successful and non-successful teams. Many other factors contribute to justify the final results.

Different styles of play may have similar final scores. The capacity to increase the variability of action and decrease the exposure to the opponent justifies acting in an indirect style of play and with a greater volume of passes (Gréhaigne, Bouthier, & David, 1997; M. Hughes & Franks, 2005). On the other hand, teams that opt to act in counter-attack or quick transition also may be successful based on evidence that suggests that a greater volume of goals scored comes from counter-attack (A. Tenga & Sigmundstad, 2011).

Our study had some limitations that must be considered. Only the top sixteen teams from the UEFA Champions League 2015–2016 were analysed. This may not characterize the overall reality of elite soccer teams. Moreover, the use of top teams may not consider the patterns that lead to unsuccessful performances.

Another limitation of our study was not considering the collective behaviour (tactical behaviour) that may justify the final score between two different styles of play. Future studies must add some observational categories that enable researchers to identify the circumstances of goals conceded and scored, trying to understand the overall tactical dynamic that led to successful or unsuccessful play during passing sequences.

Alternative techniques based on players' motion and synchronization may contribute to justify some of the values obtained from network measures (Clemente et al., 2014). These measures depend from the coordinates in the field and can identify some collective patterns, mainly considering the movements made by players in attacking and defensive moments.

In the future would be also interesting to test other general network measures namely the heterogeneity (to measure the variation of connectivity across the players), the reciprocity (to quantify the tendency of pairs of players to form mutual connections) and global centralization (to identify star-like topology) (Clemente et al., 2016). These metrics may help to identify some properties of the team and contribute to disclosure the style of play.

Despite these limitations, our study allowed us to characterize the network process of top teams from the UEFA Champions League. This is the first study that identified the general network levels of these teams. Moreover, our study also crossed classical notational variables with network measures, thus being a step forward in a more holistic view of the quantitative process that may characterize the reality of the game.

The practical implications are quite limited so far. Results from the network density may be used to characterize the capacity of the team to involve the teammates in a homogeneous way. However, the results obtained are not strong enough to recommend intervals of optimal values to be used as standard to the teams. In the case of clustering coefficient, greater values suggest the capacity of players to involve the teammates in cooperation processes. Once again, we may suggest that higher values may characterize teams with greater tendency to no centralize the passing sequences in some players, nevertheless the results are limited and can be interpreted as speculation. A study conducted in a significant sample must be conducted in the future to improve the generalization of the conclusions.

Conclusion

General network measures were used to test some characteristics of interactions between teammates during attacking building. Classical performance variables (goals and shots) had very small association levels with network density, total links and clustering coefficient. Only the percentage of ball possession revealed a positive moderate correlation with general network measures. Some of the findings did not confirm preliminary results in previous studies conducted on national teams. Future studies must cross the notational variables (classical and network measures) with qualitative observations that characterize the tactical behaviour of teams that act with different styles of play. Moreover, alternative general network measures must be used to improve the characterization of the teams and to contribute to identify some properties of the style of play.

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