Journal of Human Kinetics volume 61/2018, 141-153 DOI: 10.1515/hukin-2017-0117
Section III – Sports Training

DE GRUYTER OPEN

Variance In Prominence Levels and in Patterns of Passing Sequences in Elite and Youth Soccer Players: A Network Approach

by

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The aim of this study was to quantify the prominence levels of elite and highly competitive young soccer players. This study also analyzed the variation in general network properties at different competitive levels and periods of the season. A total of 132 matches, played by 28 teams during the 2015/2016 season, were analyzed. The results revealed significant differences in the composition of general network measures considering the competitive level ($p = 0.002$; ES = 0.077) and according to the location of the match ($p = 0.001$; ES = 0.147). There were positive correlations between network density and the final score ($\rho = 0.172$) and negative correlations between network density and goals conceded ($\rho = - 0.300$). Significant differences in the composite of centralities were found between positions ($p = 0.001$; ES = 0.293; moderate effect) and the location of the match ($p = 0.001$; ES = 0.013; no effect). This revealed that the general properties of cooperation increased with the competitive level, improved during the middle of the season and were better in home matches. Midfielders were most prominent players in elite and U19 teams in the mid-season and central defenders had the most prominent centralities in U17 and U15 during the early and late periods of the season.

Key words: *applied mathematics, graph theory, soccer, match analysis.*

Introduction

Match analysis has used a variety of techniques and methods to characterize the dynamics of soccer (Carling et al., 2005; Sarmento et al., 2014). Classical notational analysis is the most common approach to characterizing the game and quantifying the events that occur during matches (Hughes and Bartlett, 2002; Hughes and Franks, 2004). Notational analysis commonly uses observation followed by the codification and quantification of events in the game (Tenga and Sigmundstad, 2011)., however, the outcomes of this process do not explain reality in most cases (Vilar et al., 2013). New techniques and methods have thus been proposed to improve classical notational analysis (Clemente et al., 2014).

Usually, performance variables are used in notational analysis to characterize the game (Hughes and Franks, 2005). Passes, shots, receives, dribbles and possession of the ball are common performance variables used in observation and reporting (Lago-Ballesteros and Lago-Peñas, 2010; Lago-Peñas and Dellal, 2010). These variables are mostly used to analyze the variance between situational variables (match location, match status or quality of opposition) (Taylor et al., 2008). Despite the importance of such variables, current mathematical techniques have been employed to improve the ability to identify collective properties that are not analyzed in the classical notational process (Bloomfield et al., 2005; Duch et al., 2010).

One of these techniques is social network analysis (SNA) (Wasserman and Faust, 1994). SNA uses graph theory to identify the relationships between members of an organization or team (Lusher et al., 2010). The general properties of a

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Authors submitted their contribution to the article to the editorial board.
Accepted for printing in the Journal of Human Kinetics vol. 61/2018 in March 2018.

team and the centrality levels of players can be identified by different SNA measures (Clemente et al., 2016). These measures have some explicative properties regarding the outcomes and for that reason this can be considered a quantitative method with some qualitative potential (Grund, 2012).

SNA has been used as a match analysis technique in recent years (Duch et al., 2010; Grund, 2012; Yamamoto and Yokoyama, 2011). International tournaments (European Cup and FIFA World Cup) have been studied in the majority of cases (Clemente et al., 2015; Cotta et al., 2013; Duch et al., 2010; Peña and Touchette, 2012). Fewer studies have been conducted in elite soccer clubs (Clemente et al., 2015; Grund, 2012; Malta and Travassos, 2014). The most meaningful studies have been also conducted in the context of elite teams (Clemente et al., 2015; Duch et al., 2010; Yamamoto and Yokoyama, 2011).

The direction and volume of passes between teammates have been used as connecting variables in SNA applied in soccer (Clemente et al., 2016; Grund, 2012; Malta and Travassos, 2014). The most meaningful findings have suggested moderate-to-strong correlations between a team's success and greater values of network density and total links (Clemente et al., 2015; Grund, 2012). Midfielders and external defenders have been reported as the most efficient players when connecting teammates (Clemente et al., 2015; Duch et al., 2010; Malta and Travassos, 2014; Peña and Touchette, 2012). To our knowledge, youth soccer has not been properly analyzed with SNA techniques. No studies have been found that analyzed variations in network properties during a season at different competitive levels.

Therefore, the aim of this study was to analyze the general properties and centrality levels of elite and high-competitive young players over a full season. The variance in general and centrality network levels was tested between different periods of the season, competitive levels and tactical positions.

Methods

Sample

A total of 132 full official matches were analyzed in this study. A professional Portuguese soccer team that had participated in the UEFA Champions League, an under-19 elite team that also participated in the UEFA Youth League, one team of under-17 and another of under-15 were observed during the 2015/2016 season. Another 24 professional teams that had competed against the elite team were also analyzed. The adjacency matrices of direction of passes performed between teammates per each game were built and then used to compute the network measures.

Procedures

Players were firstly codified by positions. A techno-tactical assignment adopted to positional roles had been previously used in similar studies. The classification followed the tactical line-up of the team (Clemente et al., 2015; Di Salvo et al., 2007). The following positions were codified: i) goalkeeper (GK); ii) external defender (ED); iii) central defender (CD); iv) central midfielder (MF); v) external midfielder (EMF); and vi) central forward (FW). The codification was assigned by five professional soccer observers with more than five years of experience in match analysis.

The variable used in this study to classify the network was the pass between teammates. The passing sequences and the direction were codified using dedicated software. An adjacency matrix was generated per each game observed. The matrix represented the connections between a player and the teammate (Passos et al., 2011). The frequency of passes was also determined and registered in the matrix. Based on that, this study analyzed weighted digraphs (Clemente et al., 2016).

The reliability of the data collecting and codification processes was tested with a Cohen's Kappa test by adhering to a 15 day interval for re-analysis (Robinson and O'Donoghue, 2007). Results revealed a Kappa value of 0.83 for the 15% of the tested sample, thus ensuring the recommendations for the observational studies (Robinson and O'Donoghue, 2007).

The classical notational variables of goals scored and conceded and the final score were also collected. The factors of the period of the season, competitive level and location of the game were registered. Three periods of the European season (August 2015 to May 2016) were codified (early season – first three months of the season; mid-season – following four months; late season – last three months of the season). Four competitive levels were also codified (elite teams – professional soccer players in the Portuguese premier league; under-19; under-17; and under-15 teams). The locations were classified as home and away.

Network analysis

The software Social Network Visualizer (SocNetV, version 1.9) was used to compute the network measures (Kalamaras, 2014). The 156 adjacency matrices were individually imported and visualized as digraphs. The general measures of total links and network density and the centralities of outdegree, indegree and betweenness were executed in the software.

Total Links

For a weighted digraph G with n vertices, the total links index, L_D^w, of G can be computed (Rubinov and Sporns, 2010):

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

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

Total links can be a general measure of total interaction between players in a team. The maximum index for a team of 11 players is 100 (10×10 players).

Network Density

For a weighted digraph G with n vertices, the density index, Δ_D^w, of G can be computed (Wasserman and Faust, 1994):

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

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

Network density is a general measure that classifies the overall affection between players in a team. The index values vary between 0 and 1 (maximum affection between teammates).

OutDegree Centrality

Considering that n_i is the vertex of weighted digraph G with n vertices, the standardized degree centrality index, $C'^{w}_{(D-out)}(n_i)$, is the proportion of the weight of vertices that are adjacent to n_i (Opsahl et al., 2010):

$$ODC'^{w}_{(D-out)}(n_i) = \frac{k_i^{w-out}}{\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}}, \qquad (3)$$

where k_i^{w-out} is the degree centrality index of the vertex, and n_i and a_{ij} are elements of the weighted adjacency matrix of G (Clemente et al., 2016).

Outdegree centrality (ODC) shows the participation of a player during passing sequences. The relative index varies between 0 and 100 with greater values meaning greater prominence.

InDegree Centrality

The standardized degree prestige index, $P'^{w}_{(D-in)}(n_i)$, can be considered as the proportion of the weight of vertices that are adjacent to n_i (Opsahl et al., 2010):

$$IDC'^{w}_{(D-in)}(n_i) = \frac{k_i^{w-in}}{\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}}, \qquad (4)$$

where k_i^{w-in} is the degree prestige index of the vertex, and n_i and a_{ij} are elements of the weighted adjacency matrix of G (Clemente et al., 2016).

Indegree centrality (IDC) represents the prominence of a player when receiving the ball from teammates. Relative index values vary between 0 and 100 with greater values meaning greater significance.

Betweenness Centrality

For graph $G = (V, E)$, with $n_i, n_j, n_k \in V$, $i, j, k = 1, \ldots, n$, the standardized betweeness centrality index can be (Rubinov and Sporns, 2010) calculated as follows:

$$C'_b(n_k) = \frac{1}{(n-1)(n-2)} \sum_{\substack{n_i, n_j \in V \\ i \neq nj \neq k}} \frac{g_{ij}(n_k)}{g_{ij}}, \qquad (5)$$

where $g_{ij}(n_k)$ is the number of shortest paths between n_i and n_j that pass through n_k, and g_{ij} is the number of shortest paths between n_i and n_j (Clemente et al., 2016).

Betweenness centrality (BC) indicates how often a player is situated between teammates, thus showing also the players that act as a link. The relative index values vary between 0 and 100 with greater values meaning greater prominence in the mediation.

Statistical procedures

Two-way multivariate analyses of variance (MANOVA) were performed to analyse the variance of general network measures and centralities between the factors. In case of interactions between factors, a two-way analysis of variance (ANOVA) was conducted for each dependent variable. Finally, a one-way ANOVA followed by a Tukey HSD post-hoc test was carried out to analyse variance within the factor. Effect size (ES) was estimated 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 also evaluated the relationship between classical notational variables of performance (goals scored, goals conceded, final score) and network variables (total links and network density). The relationship was assessed with the Spearman correlation coefficient. The statistical procedures were carried out using SPSS software (version 23.0, Chicago, Illinois, USA); the level of significance was set at 5%.

Results

General measures

Multivariate MANOVA evaluated the variance of general measures between the competitive level, period of the season and location of the match. Results revealed significant differences in the composite of general measures in the competitive level (p = 0.002; ES = 0.077; *minimum effect*) and location of the match (p = 0.001; ES = 0.147; *minimum effect*). No statistically significant differences were found in the period of the season (p = 0.124; ES = 0.027; *no effect*). Significant interaction was found in the cross factor competitive level*location (p = 0.005; ES = 0.067; *minimum effect*). No significant interactions were found in competitive level*period of the season (p = 0.389; ES = 0.046; *minimum effect*), period of the season*location (p = 0.706; ES = 0.008; *minimum effect*) and competitive level*period of the season*location of the match (p = 0.116; ES = 0.065; *minimum effect*).

Two-way ANOVA revealed statistically significant difference in network density (p = 0.030; ES = 0.065; *minimum effect*) in the interaction competitive level*location.

One-way ANOVA tested the variance of total links and network density between competitive levels. Significant differences were found in total links (p = 0.002; ES = 0.093; *minimum effect*). Greater values of total links were found in elite teams (84.15). Results are presented in Table 1.

The variance of total links and network density between periods of the season were also evaluated. Significant differences were found in total links (p = 0.038; ES = 0.042; *minimum effect*). Greater values of total links were found in the mid-season (82.49). Descriptive statistics can be found in Table 2.

One-way ANOVA tested the variance of general measures between locations of the match. Significant differences were found in total links (p = 0.001; ES = 0.082; *minimum effect*) and network density (p = 0.001; ES = 0.142; *minimum effect*). Greater values of total links and network density were found in home games (83.60 and 0.76, respectively). Results are presented in Table 3.

The relationships between the final score (ratio scale variable: 1 – loss; 2 – draw; and 3 – win) and variables of goals scored, goals conceded, total links and network density were tested with Spearman's ρ. There were positive correlations between network density and the final score (ρ = 0.172), while negative correlations were observed between network density and goals conceded (ρ = - 0.300). Table 4 shows the output produced.

Centrality measures

Multivariate MANOVA tested the variance of four factors (positions, competitive level, period of the season and location of the match) in the centrality measures of players. Significant differences in the composite of centralities were found between positions (p = 0.001; ES = 0.293; *moderate effect*) and location of the match (p = 0.001; ES = 0.013; *no effect*). No statistically significant differences were found between competitive levels (p = 0.081; ES = 0.003; *no effect*) and period of the season (p = 0.186; ES = 0.003; *no effect*). Significant interactions were observed in the cross factors of competitive level*position (p = 0.001; ES = 0.068; *minimum effect*), competitive level*location (p = 0.035; ES = 0.004; *no effect*), period of the season*position (p = 0.009; ES = 0.011; *no effect*) and location*position (p = 0.001; ES = 0.010; *no effect*).

Two-way ANOVA revealed statistical differences in the cross factors competitive level*position for the measures of ODC (p = 0.001; ES = 0.100; *minimum effect*), BC (p = 0.001; ES = 0.062; *minimum effect*) and IDC (p = 0.001; ES = 0.106; *minimum effect*); period of the season*position in the ODC variable (p = 0.005; ES = 0.016; *no effect*); and location*position in the IDC variable (p = 0.001; ES = 0.013; *no effect*). All the interactions were detected with the position factor. Based on that, one-way ANOVA tested the variance of centrality levels between positions (Table 5). Moreover, a split file evaluated the variance of centrality levels per position at different competitive levels (Figure 1), periods of the season (Figure 2) and location of the match (Figure 3).

Significant differences of centrality measures were observed between positions. Central defenders had greater average values of % ODC (12.37) and % BC (4.61). Midfielders presented a greater average value of % IDC (10.34). The lowest values were found in goalkeepers and forwards.

A one-way ANOVA tested the variance of % ODC, % BC and % IDC per position in each competitive level (Figure 1). Significant differences of % ODC were found at the elite level (p = 0.001; *ES* = 0.486; *moderate effect*), in U19 (p = 0.001; *ES* = 0.524; *moderate effect*), U17 (p = 0.001; *ES* = 0.572; *moderate effect*) and U15 (p = 0.001; *ES* = 0.707; *strong effect*). Furthermore, significant differences of % BC were observed at the elite level (p = 0.001; *ES* = 0.147; *minimum effect*), in U19 (p = 0.001; *ES* = 0.332; *moderate effect*), U17 (p = 0.001; *ES* = 0.263; *moderate effect*) and U15 (p = 0.001; *ES* = 0.385; *moderate effect*). Finally, significant differences of % IDC were found at the elite level (p = 0.001; *ES* = 0.355; *moderate effect*), in U19 (p = 0.001; *ES* = 0.436; *moderate effect*), U17 (p = 0.001; *ES* = 0.402; *moderate effect*) and U15 (p = 0.001; *ES* = 0.550; *moderate effect*).

A one-way ANOVA tested the variance of % ODC, % BC and % IDC per position in each period of the season (Figure 2). Significant differences of % ODC were found in the early season (p = 0.001; *ES* = 0.563; *moderate effect*), middle season (p = 0.001; *ES* = 0.484; *moderate effect*) and late season (p = 0.001; *ES* = 0.534; *strong effect*). Also significant differences of % BC were observed in the early season (p = 0.001; *ES* = 0.218; *minimum effect*), middle season (p = 0.001; *ES* = 0.255; *moderate effect*) and late season (p = 0.001; *ES* = 0.239; *minimum effect*). Finally, statistically significant differences of % IDC were found in the early season (p = 0.001; *ES* = 0.386; *moderate effect*), middle season (p = 0.001; *ES* = 0.376; *moderate effect*) and late season (p = 0.001; *ES* = 0.364; *moderate effect*).

A one-way ANOVA tested the variance of % ODC, % BC and % IDC per position in each location of the match (Figure 2). Significant differences of % ODC were found in home (p = 0.001; *ES* = 0.602; *moderate effect*) and away games (p = 0.001; *ES* = 0.437; *moderate effect*). Furthermore, statistically significant differences of % BC were observed in home (p = 0.001; *ES* = 0.313; *moderate effect*) and away games (p = 0.001; *ES* = 0.193; *minimum effect*). Finally, significant differences of % IDC were found in home (p = 0.001; *ES* = 0.474; *moderate effect*) and away games (p = 0.001; *ES* = 0.285; *moderate effect*).

Table 1

Descriptive statistics (mean ± SD; [CI95%]) and analysis of variance of general measures between competitive levels.

	Elite	U19	U17	U15	*p*	*ES*
Total Links	84.15 ± 9.47[d] [81.66-86.63]	80.43 ± 7.05 [77.77-83.08]	81.81 ± 9.85 [78.77-84.86]	76.56 ± 8.35[a] [73.60-79.51]	0.002	0.093 *minimum effect*
Network Density	0.74 ± 0.9 [0.72-0.76]	0.73 ± 0.6 [0.71-0.76]	0.74 ± 0.9 [0.72-0.77]	0.70 ± 0.8 [0.67-0.72]	0.060	0.047 *minimum effect*

Significant differences from Elite[a]; U19[b]; U17[c]; and U15[d] for $p < 0.05$

Table 2

Descriptive statistics (mean ± SD; [CI95%]) and analysis of variance of general measures between periods of the season.

	Early season	Mid-season	Late season	*p*	*ES*
Total Links	81.76 ± 8.23 [79.04-84.49]	82.49 ± 8.76[c] [80.34-84.65]	78.23 ± 9.74[b] [75.66-80.81]	0.038	0.042 *Minimum effect*
Network Density	0.73 ± 0.08 [0.71-0.76]	0.74 ± 0.08 [0.72-0.76]	0.71 ± 0.09 [0.69-0.73]	0.144	0.025 *no effect*

Significant differences from early season[a]; middle season[b]; and late season[c] for $p < 0.05$

Table 3

Descriptive statistics (mean ± SD; [CI95%]) and analysis of variance of general measures between locations of the match.

	Home	Away	*p*	*ES*
Total Links	83.60 ± 6.91* [81.65-85.55]	78.42 ± 10.20* [76.47-80.37]	0.001	0.082 *minimum effect*
Network Density	0.76 ± 0.06 [0.74-0.78]	0.70 ± 0.09 [0.68-0.72]	0.001	0.142 *minimum effect*

**Significant differences for $p < 0.05$*

Table 4

Correlation values (Spearman's ρ) between general network measures and performance variables.

	Final score	Goals scored	Goals conceded
Total links	0.050	0.116	- 0.039
Network density	0.172*	0.101	- 0.300**

**correlation is significant at the 0.05 level; **correlations is significant at the 0.01 level*

Table 5

Descriptive statistics (mean ± SD; [CI95%]) and analysis of variance of general measures between centrality measures.

	GK	ED	CD	MF	EMF	FW	*p*	*ES*
% ODC	2.88 ± 1.57 [2.40-3.37] [b-f]	9.00 ± 2.34 [8.66-9.34] [a,c-f]	12.37 ± 3.55 [12.03-12.71] [a-b,e-f]	11.89 ± 4.13 [11.61-12.18] [a-b,e-f]	7.25 ± 2.57 [6.91-7.59] [a-d,f]	4.87 ± 2.03 [4.43-5.32] [a-e]	0.001	0.513 *moderate effect*
% BC	0.41 ± 0.52 [0.05-0.77] [b-f]	2.92 ± 2.26 [2.66-3.17] [a,c-f]	4.61 ± 2.90 [4.35-4.86] [a-b,d-f]	3.96 ± 2.61 [3.75-4.18] [a-c,e-f]	2.29 ± 2.03 [2.03-2.55] [a-d,f]	1.60 ± 1.73 [1.26-1.93] [a-e]	0.001	0.235 *minimum effect*
% IDC	3.43 ± 2.03 [2.98-3.88] [b-f]	9.91 ± 2.41 [9.59-10.23] [a,f]	10.19 ± 2.93 [9.87-10.51] [a,f]	10.34 ± 3.51 [10.08-10.61] [a,f]	9.85 ± 2.98 [9.53-10.17] [a,f]	5.91 ± 2.17 [5.50-6.33] [a-e]	0.001	0.369 *moderate effect*

Significant differences from GK[a]; ED[b]; CD[c]; MF[d]; EMF[e]; and FW[f] for $p < 0.05$

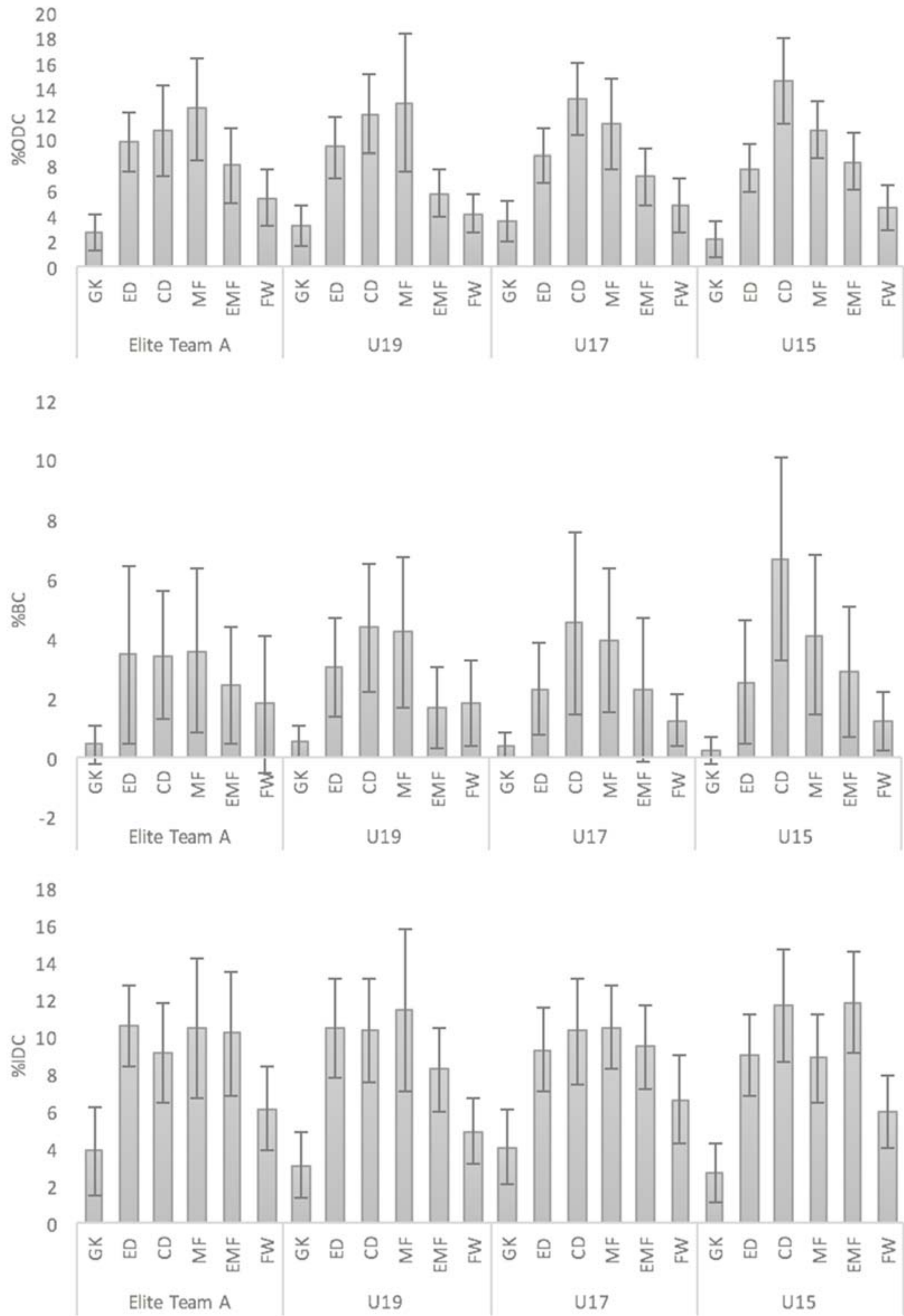

Figure 1

Mean and SD of % ODC per position at each competitive level.

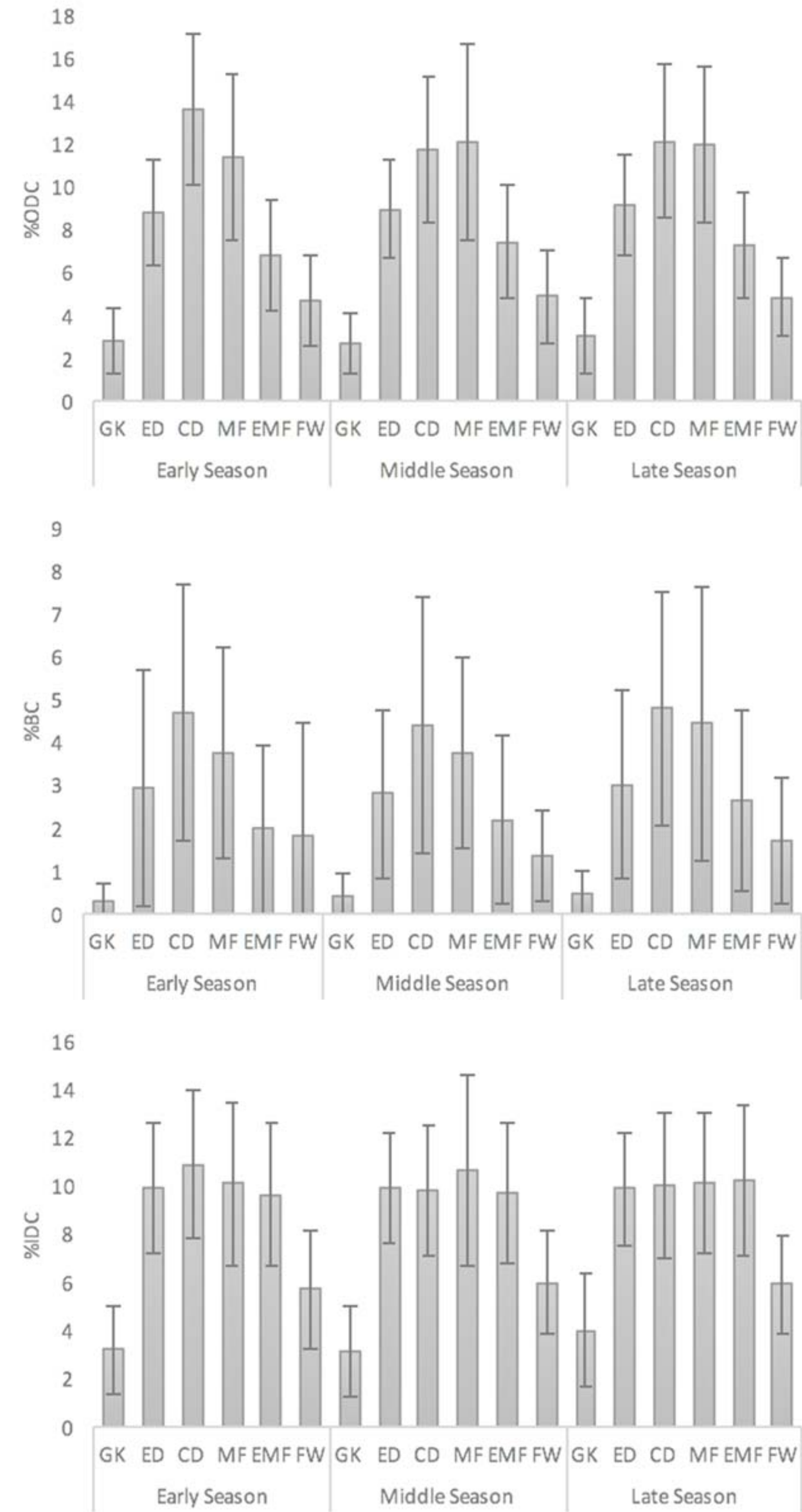

Figure 2

Mean and SD of % ODC per position in each period of the season.

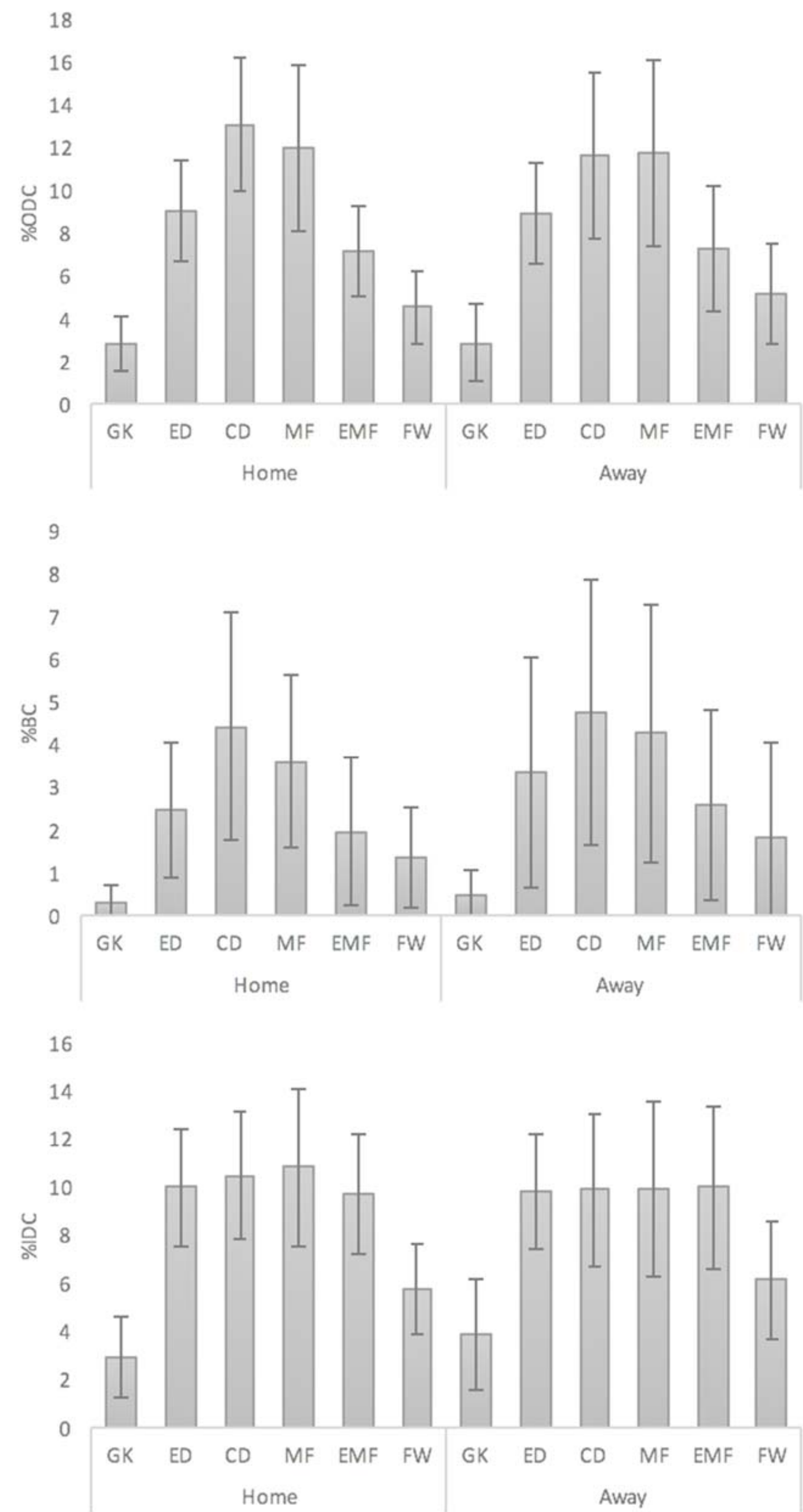

Figure 3

Mean and SD of % ODC per position in home and away matches.

Discussion

This study used the network approach to quantify the prominence levels of elite and high competitive young soccer players and at the same time to analyze the variation in general network properties at different competitive levels and periods of the season. There are few studies that have analyzed this subject and its impact on different age groups within the same club.

The results of this study show significant differences between general network measures at the competitive level and according to the location of the match. These differences could be explained by the age differences and their eventual correlation with variance in the overall level of biological maturation (Balyi and Hamilton, 2004; Malina et al., 2004). The location of the match and the increase in general properties of player's cooperation in home matches could be explained by greater identification and self-assurance/confidence when the athlete plays in an environment to which they are already accustomed, when compared to matches played away from home (Legaz Arrese et al., 2013). Nevertheless, we cannot exclude the possibility that changes in the cooperation level also occur in conjunction with a higher competitive level associated, of course, with the respective increase in athlete's age; this is also clear during the middle of the season (which leads us to reflect on the importance of training outcomes on player's performance, as well as fatigue and the increasing difficulty level in the final stages of the season).

The correlation tests of performance variables and network characteristics suggest two conclusions from this study: a) there were positive correlations between network density and the final score; b) there were negative correlations between network density and goals conceded. These two conclusions, when accompanied by the general positive correlation of total links and density with the level of competition (except for the U19 team), could suggest a correlation between team success, network density and total links (Clemente et al., 2015; Grund, 2012). It is important to emphasize, however, that there are differences between the competitions analyzed, regarding the quality of the opponents and the respective competitions in general, which could influence these results. This would be a pertinent starting point for future studies within this subject.

This study provides very interesting results with respect to the centrality levels and in the analysis of the most prominent players regarding the connection between teammates. Bearing in mind that (although as far as we know, youth soccer has not been properly analyzed with SNA techniques and this work includes elite and youth players results) midfielders and external defenders have been reported as the most prominent players connecting teammates (Duch et al., 2010; Peña and Touchette, 2012), one interesting finding in this study was that central defenders showed the biggest average values of % ODC and % BC and midfielders had the greatest average values of % IDC. Although future work is required to confirm these results, this could be explained by the fact that we analyzed different age groups within the same club, and so, identified with a similar game model and a comparable general player's profile. This could explain these values considering that central defenders are very prominent in offensive build-up actions and midfielders ensure the connection/maintenance of ball possession between different teammates or sectors within the team (Clemente et al., 2015).

More specifically, within each age group, we can also verify that in elite and U19 teams, midfielders are the most prominent players. In U17 and U15, central defenders had most prominent centralities. When considering the phase of the season, midfielders showed the most prominent centralities in the middle season and central defenders had the greatest prominent centralities during the early and closing periods of the season. This can be explained by specificities such as the need to score and the kind of pressure from opposing teams at times in the season when winning points is more important. This should be carefully analyzed in future studies.

Finally, although it is necessary to emphasize the need for further and future studies, the differences revealed in this work regarding centrality levels throughout the season and per position, and the fact that central defenders had greater prominent centralities during the early and closing periods of the season compared with the greater prominent centralities of midfielders during the middle of the season, could be explained by the tactical learning process of the teams in the first stages of the season (slow build-up and preoccupation with consolidating the offensive method and process); the fact that the same situation also happened in the final period of the season could be explained by the increase of the match difficulty level (final phases in youth teams competitions). Midfielders showed more prominent centralities in the middle season, probably due to the consolidation of the offensive process, according to the game model adopted by the club. These are simple hypotheses that need further studies for confirmation.

Conclusions

We used SNA to identify the general properties and centrality levels of different players. The main finding of this study was a moderate-to-strong correlation between general network properties and performance variables of the final score and goals conceded. It was also found that elite teams had greater values for total links and network density than younger teams, and that playing at home also significantly increased the homogeneity of relationships between teammates during attacking plays. Youth players had lower levels of network density, thus suggesting a great tendency to be heterogeneous during passing sequences. On the other hand, values of elite players pointed out a more homogeneous tendency to perform passing sequences during attacks. Centrality measures revealed that positions with greater prominence during attacking plays were central defenders and midfielders, and that their prominence was variable during different periods of the season. All these findings are new outcomes in the field of match analysis, as a result of using network measures, and future studies should confirm these findings.

Acknowledgements

The authors would like to thank BenficaLab and soccer players for their participation. This study was carried out within the scope of R&D Unit 50008, financed by UID/EEA/50008/2013.

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