# Multiple Regression Analysis For Competitive Performance Assessment Of Professional Soccer Players

Radakovic Radivoje[1,2], Dasic Lazar[1,*], Dopsaj Milivoj[3], Filipovic Nenad[4]

[1]Institute for Information Technologies, University of Kragujevac, Kragujevac, Serbia

[2]Serbia U21 National Football Team

[3]Faculty for Sport and Physical Education, University of Belgrade, Belgrade, Serbia

[4]Faculty of Engineering, University of Kragujevac, Kragujevac, Serbia

*corresponding author: Lazar Dašić, Institute for Information Technologies, University of Kragujevac, Kragujevac, Serbia. E-mail: lazar.dasic@kg.ac.rs

**Abstract**

**BACKGROUND:**

Being in peak physical condition and having specific motor abilities are necessity for every top-level soccer player in order to achieve success in competition. In order to correctly assess soccer players' performance, this research uses laboratory and field measurements, as well as results of competitive performance obtained by direct software measurements of players' movement during the actual soccer game.

**OBJECTIVE:**

The main goal of this research is to give insight into the key abilities that soccer players need to have in order to perform in competitive tournaments. Besides training adjustments, this research also gives insight into what variables need to be tracked in order to accurately assess the efficiency and functionality of the players.

**METHODS:**

The collected data need to be analyzed using descriptive statistics. Collected data is also used as input for multiple regression models that can predict certain key measurements: total distance covered, percent of effective movements and high index of effective performance movements.

**RESULTS:**

Most of the calculated regression models have high predictability level with statistically significant variables.

**CONCLUSIONS:**

Based on the results of regression analysis it can be deduced that motor abilities are important factor in measuring soccer player's competitive performance and team's success in the match.

**Keywords:** effective movement, motor abilities, soccer player's competition performance, total distance covered

# 1. Introduction

Using software systems for tracking players during the soccer game gives exact information about players' movements and field awareness which enables sport experts and coaches to make observations and predictions, as well as training adjustments that would further develop players accordingly to their needs and abilities.

Modern soccer is characterized with a large number of complex movements that require players to constantly acquire information and make decisions in order to anticipate opponents' attacks and respond to them in adequate manner. Soccer is often regarded as an acyclic sport where rhythm and intensity of the game is regularly changing and where players' movements have a lot of sudden direction and speed changes. It is estimated that soccer game is structured out of periods of maximum intensity (lasting on average 2-8 seconds) followed by submaximal resting periods that usually last 30-90 seconds (1,2). Also, the top players in modern soccer perform an increasing number of prolonged sprinting movements (RSA), pushing the limits of speed and distance covered at maximum speeds (35-38 km/h). By analysis of the matches at the World Cup in Qatar, it is confirmed that players endure increasingly more duels and aerial duels with higher intensity and power. Because of all of the aforementioned, success in soccer competitions is dependent on players being in a peak physical condition with high fatigue tolerance and quick recovery rates.

Having specific motor abilities is necessity for every top-level soccer player in order to achieve success in competition. Goal of these specific motor abilities is to provide answers to different challenges unique to soccer game. During a single soccer game, top-level players on average do 50 sudden accelerations and decelerations that require very intensive concentric and eccentric contractions of thigh muscles, hamstring muscles and their synergists.

Numerous research, that differ in both methodology and used imaging data, have been conducted on the topic of plaque segmentation. On MRI images, Clarke et al. [7] achieved satisfactory results using minimum distance classifier algorithm. On the other hand, Hofman et al. [8] tested multiple supervised learning algorithms on MRI images, but every model had problem correctly classifying calcification component. Rezaei et al. [9] proposed a set of algorithms for segmentation, feature extraction, and plaque type classification. A hybrid model using k-nearest neighbor (KNN) and the fuzzy c-means (FCM) algorithm was used to accurately segment the plaque area of intravascular ultrasound images. Perhaps, the best results were achieved by Athanasiou et al. [10] who used random forest algorithm for classification of features that were extracted from Optical coherence tomography (OCT) imaging data. They attained 0.71 and 0.81 Jaccard similarity coefficient for lipid and calcification component, respectively.

Numerous research on the topic of soccer players' performance assessment, that differ in both methodology and data used, have been conducted in recent years. Lago-Penas et al. have analyzed male soccer competition trying to identify statistics in the matches played that shows difference between winning, drawing and losing teams (3). Using discriminant analysis, they discovered that key variables that separate winning, drawing and losing teams are: total shots, shots on goal, effectiveness, passes, successful passes, ball possession, yellow and red cards. Bloomfield et al. evaluated the physical demands of English Football Association (FA) Premier League soccer of three different positional classifications (defender, midfielder and striker) (4). It was discovered that player's position had great influence on percent of purposeful movement time spent of sprinting, running and jumping. This study showed that players at different positions have different physical demands. Reilly, Rienzi et al., Bangsbo have all concluded that elite defenders and attackers have similar average distance covered (10-10.5 km), while midfielders cover significantly more distance (11.5 km) (5,6,7). Also, it was discovered that defenders and midfielders are most often engaged in activities of low to medium intensity, while attackers perform both more and longer sprints (8). On the other hand, defenders perform more backward and lateral movements than attackers, which use 20-40% more energy that running forward (9). Bloomfield et al. recently identified major differences in age, height, body weight and body mass index between top level soccer players at different positions (10). Buttifant et al. stated that agility is one of the most important factors of the game that need to be monitored in order to completely represent demands of the soccer game (11). Besier et al. discovered that players need to be put through certain training and prehabilitation processes in order to perform at the top level (12).

This paper gives insight into the key abilities that soccer players need to have in order to perform in competitive tournaments. This provides useful information, to both coaches and players, that could be used to optimize and control training plan and methodology. Beside training adjustments, this research also gives insight into what variables need to be tracked in order to accurately assess the efficiency and functionality of the players during the monitored games.

# 2. Materials and methods

## 2.1. Dataset

Total of seventy top-level soccer players participated in the study, all of whom were playing for teams competing in the Serbian Super Liga (country's top soccer league competition): FK Red Star Belgrade, OFK Beograd and FK Radnički 1923. Beside these soccer clubs, players of Serbia national team (ranked 21 on FIFA rankings) participated in the study as well. Data was gathered during thirty soccer games played across Serbian Super Liga and UEFA club competitions, as well as games played by Serbia national team in 2018 FIFA World Cup qualification.

Data consists of 34 features split into three different groups.

Morphological characteristics:

1. Body weight (kg) – BW
2. Body height (cm) – BH
3. Body mass index (kg/m2) – BMI
4. Body fat mass (%) – BFM

5. Body muscle mass (%) – BMM

Characteristics used to analyze motor abilities of a participant:

1. Starting acceleration for 10 meters without the ball (m/s2) – ACC10mWOB
2. Starting acceleration for 20 meters without the ball (m/s2) – ACC20mWOB
3. Starting acceleration for 30 meters without the ball (m/s2) – ACC30mWOB
4. Time needed to cover 10 meters without the ball (s) – V10mWOB
5. Time needed to cover 20 meters without the ball (s) – V20mWOB
6. Time needed to cover 30 meters without the ball (s) – V30mWOB
7. Starting acceleration for 10 meters with the ball (m/s2) – ACC10mWB
8. Starting acceleration for 20 meters with the ball (m/s2) – ACC20mWB
9. Starting acceleration for 30 meters with the ball (m/s2) – ACC30mWB
10. Time needed to cover 10 meters with the ball (s) – V10mWB
11. Time needed to cover 20 meters with the ball (s) – V20mWB
12. Time needed to cover 30 meters with the ball (s) – V30mWB
13. Acceleration index 10/20 meters – AI10/20m (represent quotient of dividing ACC10mWB with ACC20mWB)

14. Acceleration index 10/30 meters – AI10/30m (represent quotient of dividing ACC10mWB with ACC30mWB)
15. Agility without ball on zig-zag test (s) – ZZWOB
16. Agility with ball on zig-zag test (s) – ZZWB
17. Index of ball control skills – IBCS (represent quotient of dividing ZZWB with ZZWOB)
18. Jump without arm swing (cm) – JWOS
19. Jump with arm swing (cm) – JWS
20. 10 repeated jumps (cm) – RJ
21. Aerobic power on Shuttle Run test (m / ml/kg/min) – SHR

Characteristics used to determine soccer player's competition performance:

1. Total distance covered (m) – TD
2. Total distance covered with speeds in the range 0-8 km/h (m) – TDW
3. Total distance covered with speeds in the range 8-15 km/h (m) – TDLI
4. Total distance covered with speeds on anaerobic threshold in the range 15.1-19 km/h (m) – TDAT
5. Total distance cover with speeds on VO2max in the range 19.1-23 km/h (m) – TDVO2max
6. Total distance cover with submaximal and maximal speed over 23 km/h (m) – TDMI

7. Percent of effective movements (%) - %EM (represents percent of distance covered with speeds over anaerobic threshold relative to the total distance covered)
8. High index of effective performance movements – HIEPM (represents index of high intensity movements relative to the technical/tactical tasks)

Third group of features was collected during games by using BioIRC Tracking Motion software system, that employs two identical highspeed cameras in full HD resolution and one control camera with "high speed" capabilities. Interface of the tracking software is showed in the Figure 1a. Software part of the system for digital processing of video recordings (tracking of players movements) is based on determining the level of similarity of the object's color statistical distribution (13). This software allows linear, individual and whole team tracking of current position and history of movement of their own and opposing players in any moment or period of time of the analyzed soccer match (14). Figure 1b shows total trajectory of a single player during a halftime with different classifications based on movement intensity. This tracking gives coaches and experts insight into player's movement tendencies and play development in the field, which are valuable inputs in analysis and correction of game and training plan (15). Figure 2a shows quantitative measurements of player's movement intensity during a halftime and Figure 2b shows only the player's movements with the high intensity.

"FIGURE 1 SHOULD BE PLACED HERE"

"FIGURE 2 SHOULD BE PLACED HERE"

In order to determine player's performance, collected data need to be analyzed. In order to summarize given dataset, descriptive statistics were used in order to calculate measures of central tendency and measures of dispersion: mean (X), standard deviation (SD), standard absolute error (Std. Error Aps.), standard relative error (Std. Error Rel.), coefficient of variation (cV%), minimum (Min) and maximum (Max) values.

In order to check equality of probability distribution, Kolmogorov–Smirnov nonparametric test was used. To determine shape of the distribution skewness (SKW) and kurtosis (KRT) were calculated.

**2.1. Descriptive statistics of research participants' morphological variables**

Descriptive statistics for the whole dataset consisting of 70 top-level soccer players are given in the Table 1. Looking at the results, it can reliably be stated that dataset is homogenous. Coefficient of variation (cV%) is in the range of 6.21% (for variable BMM) and 45.9% (for variable BMI).

"TABLE 1 SHOULD BE PLACED HERE"

**2.2 Descriptive statistics of research participants' motor abilities variables**

Coefficient of variation results (cV%) are in the range of 4.09% (for variable V30mWOB) and 53.81% (for variable V10mWOB), so it is clear that results of all tested top-level soccer players' motor abilities are part of the homogenous set. Also, it can be deduced that measured variables are highly reliable given that cV% does not go over 12.52%, except in the case of V10mWOB (cV% = 53.81%). Looking at the results for skewness that are in the range of -0.924 for variable JWOS and 0.534 for variable JWS, it is clear that results follow normal distribution. In Table 2, basic descriptive statistics for motor abilities variables for the all players in the dataset are shown:

"TABLE 2 SHOULD BE PLACED HERE"

### 2.3 Descriptive statistics of research participants' competition performance variables

Coefficient of variation results (cV%) are in the range of 9.02% (for variable TDW) and 41.61% (for variable HIEPM), so it can be deduced that results of all tested top-level soccer players' competition performance variables are part of the homogenous set. Also, it can be deduced that measured variables are highly reliable given that cV% does not go over 41.61%. Results of skewness are in the range of -0.816 (for variable TDW) and 0.894 (for variable HIEPM) which implies normal distribution. Only in the case of TDMI variable, slight right skewness can be observed (SKW=1.537). By looking at kurtosis variable, most of variables follow platykurtic distribution, except for variable HIEPM that closely follows normal distribution (KRT=2.34) and variable TDMI that follows leptokurtic distribution (KRT=4.22). In Table 3, basic descriptive statistics for competition performance variables for the all players in the dataset are shown:

"TABLE 3 SHOULD BE PLACED HERE"

### 2.4 Regression analysis

Determination of the degree of relationship between dependent and independent variables was accomplished by using one-dimensional and multi-dimensional correlations – Multiple regression analysis. General degree of correlation between top-level players' competition performance, motor abilities and morphological variables is calculated by using multiple Z-scores – centroid method. Statistical significance of a correlation coefficient is calculated with 95% confidence interval and p-value<0.05.

## 3. Results

Using top-level soccer players' motor abilities characteristics as independent variables, we are able to determine relationship with key competition performance characteristics: total distance covered (TD), percent of effective movements (%EM) and high index of effective performance movements (HIEPM). Best regression prediction models were chosen based on two criteria:

1. By the percent of correct model predictions about player movements during the game
2. By the least error of the estimate, or the most precise prediction model

### 3.1 Regression analysis for TD prediction based on participants' motor abilities variables

Results of regression analysis using motor abilities variables for predicting total distance covered during a game based on the whole dataset (all players on the pitch) show that general regression model achieved Adjusted R Square of 49.5% with the Standard Error of the Estimate of ± 727.1 meters. These results are statistically significant given F-value of 5.20 with the p-value=0.001 on ANOVA test. Table 4 shows ANOVA test results for the best multiple regression model predicting total distance covered:

"TABLE 4 SHOULD BE PLACED HERE"

Optimal regression model used following independent variables: ACC10mWOB, ACC20mWOB, ACC30mWOB, ZZWB, ZZWOB, AI10/20m and IBCS. Table 5 shows coefficients for aforementioned regression model:

"TABLE 5 SHOULD BE PLACED HERE"

**3.2 Regression analysis for HIEPM prediction based on participants' motor abilities variables**

Optimal regression model is statistically significant given F-value of 4.13 with the p-value=0.004 on ANOVA test. Results of regression analysis using motor abilities variables for predicting high index of effective performance movements based on the whole dataset (all players on the pitch) show that general regression model achieved Adjusted R Square of 45.5% with the Standard Error of the Estimate of ± 13006.43. In the Table 6 ANOVA test results for the best multiple regression model predicting HIEPM are shown:

"TABLE 6 SHOULD BE PLACED HERE"

Following motor abilities characteristics were chosen as regression model's independent variables: ACC10mWOB, ACC20mWOB, ZZWB, ZZWOB, AI10/20m, JWOS, JWS and RJ. Table 7 shows coefficients for aforementioned regression model:

"TABLE 7 SHOULD BE PLACED HERE"

**3.3 Regression analysis for %EM prediction based on participants' motor abilities variables**

Results of regression analysis using motor abilities variables for predicting percent of effective movements based on the whole dataset (all players on the pitch) show that general regression model achieved Adjusted R Square of 46.3% with the Standard Error of the Estimate of ± 40.6 %. Optimal regression model is statistically significant given F-value of 5.31 with the p-value=0.001 on ANOVA test. In the Table 8 6 ANOVA test results for the best multiple regression model predicting %EM are shown:

"TABLE 8 SHOULD BE PLACED HERE"

Described model uses following independent variables: ACC10mWOB, ACC20mWOB, ZZWB, ZZWOB, AI10/20m, JWOS. Table 9 shows coefficients for aforementioned regression model:

"TABLE 9 SHOULD BE PLACED HERE"

## 4. Discussion

The results of regression analysis are based on the fact that motor abilities represent basic measurement of potential/quality of player's competitive performance, even though they are not the only factor in achieving success in a soccer match. In the competitive conditions of the soccer game, it is necessary to have high level of motor abilities and physical fitness, in order to be able to: respond to sudden changes of tempo and unpredictable high-intensity technical movements, anticipate events on the field and react to them in a timely manner, complete technical/tactical tasks, position yourself correctly etc.

Negative values of coefficient β shows that variables ACC10mWOB, ZZWOB and IBCS are good predictors. This means that player needs to have: good speed and acceleration in order to stop actions of the opposite team on the short distances (ACC10mWOB, ACC20mWOB, AI10/20m), good agility in order to quickly change speed and direction of their movement (ZZWOB, ZZWB). Given that modern soccer requires of all players, regardless of a position, to be involved in organization and build-up of the plays with ball possession, it is necessary that players have great explosiveness and acceleration during the aerial and ground duels.

Using Tracking Motion software system to collect information and regression models to analyze relations between soccer player's motor abilities and his competitive performance, it is possible to use this system for:

1. Diagnostics – To evaluate current form of the players

2. Correction of training program – To profile training methods and regiments and predict projected level of competitive performances
3. Prognostic capabilities – To predict competitive results by evaluating current competitive performance of the team

## 5. Conclusions

Based on the results of regression analysis it can be deduced that motor abilities are important factor in measuring soccer player's competitive performance and team's success in the match. In the modern soccer, especially at the top level, it is necessary to have players with high level of motor abilities in order to adequately respond to game's physical and technical/tactical challenges. It is especially necessary to be able to perform numerous high-intensity movements and skills at the speeds that exceed 18 km/h.

It can be stated that correlation between top-level soccer players' level of competitive performance and their general and specific physical conditioning and skills has been confirmed. Most of the calculated regression models have high predictability level of over 80% with statistically significant variables.

Based on the results of regression analysis, it can be stated that internal reliability of players' total distance covered during first and second half of the soccer game, both for team as a whole and per position, is very high. Movements of the whole team (Cronbach $\alpha$ = 0,946), defenders (Cronbach $\alpha$ = 0,950) and attackers (Cronbach $\alpha$ =

0,898) have very high reliability, while movements of midfielders (Cronbach $\alpha$ = 0,785) have high reliability. This mean that software analysis achieves high sensitivity with sufficient coefficients of both internal and external reliability. Also, this software analysis system represents highly precise analytical tool with exact parameters.

The applicative and innovative importance of this work is reflected in the fact, that in an exact and useful way, it connects the results of soccer players' performance obtained by laboratory and field measurements with the results of competitive performance obtained by direct software measurements of player movements during the game. Of particular importance is the precise determination of correlations between variables for each line and for the team as a whole. This procedure combines the analytical-diagnostic procedure and predictive factors of morpho-functional and motoric potentials for success in soccer.

Results of this research should be looked as indicators that could be used to follow players' conditioning and competitive performance, as well as to control and optimize training program.

Further studies will focus on obtaining larger dataset by analyzing more soccer games of different teams (more players), with variety in terms of technical/tactical tasks and a level of competition. This would provide the possibility to confirm correlation between variables on a larger sample.

## Acknowledgments

The authors have no acknowledgments.

## Conflict of interest

The authors declare that they have no conflict of interest.

## Funding

The research was funded by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, contract number [Agreement No. 451-03-47/2023-01/200378.]. This research is also supported by the project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 952603 (SGABU project). This article reflects only the author's view. The Commission is not responsible for any use that may be made of the information it contains.

## Data availability

Dataset used in this research is a private property of the soccer teams that were part of the study. Dataset contains sensitive information that could give insight into the identity and abilities of soccer players, most of which are still active professionals in the highest soccer competitions.

## Ethics statement

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants involved in the study. All of the measuring and testing in the research have been performed in accordance with the standards of the Internationa Biological Program (IBM) and Union of European Football Associations (UEFA).

## References


1. Mohr M, Krustrup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. Journal of sports sciences. 2003; 21(7): 519-528.

2. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri FM. Variation in top level soccer match performance. International journal of sports medicine. 2007; 28(12): 1018-1024.

3. Lago-Peñas C, Lago-Ballesteros , Rey. Differences in performance indicators between winning and losing teams in the UEFA Champions League. Journal of human kinetics. 2011; 27(1): 135-146.

4. Bloomfield J, Polman , O'Donoghue. Physical demands of different positions in FA Premier League soccer. Journal of sports science & medicine. 2007; 6(1): 63.

5. Bangsbo J. Energy demands in competitive soccer. Journal of sports sciences. 1994; 12(sup1): S5-S12.

6. Reilly T. Energetics of high-intensity exercise (soccer) with particular reference to fatigue. Journal of sports sciences. 1997; 15(3): 257-263.

7. Rienzi E, Drust B, Reilly T, Carter JE, Martin A. Investigation of anthropometric and work-rate profiles of elite South American international soccer players. Journal of sports medicine and physical fitness. 2000; 40(2): 162.

8. O'Donoghue P. Time-motion analysis of work rate in elite soccer. In World Congress of Notational Analysis of Sport IV; 1998; Porto, Portugal: University of Porto Press. p. 65-71.

9. Williford HN, Olson MS, Gauger SABINE, Duey WJ, Blessing DL.

Cardiovascular and metabolic costs of forward, backward, and lateral motion. Medicine and science in sports and exercise. 1998; 30(9): 1419-1423.

10. Bloomfield J, Polman RCJ, Butterly R, O'Donoghue PG. An analysis of quality and body composition of four European soccer leagues. Journal of Sports Medicine and Physical Fitness. 2005; 45: 58-67.

11. Buttifant D, Graham K, Cross K. Agility and speed in soccer players are two different. In Spinks W, Reilly T, Murphy A, editors. Science and football IV. London: Routledge; 2002. p. 329-332.

12. Besier TF, Lloyd DG, Cochrane JL, Ackland TR. External loading of the knee joint during running and cutting maneuvers. Medicine and science in sports and exercise. 2001; 33(7): 1168-1175.

13. Vulović R, Radaković R, Peulić A, Nikolić D, Filipović N. Method for software tracking and analysis of players motion during a football match. In International Conference FSFV; 2012; Belgrade. p. 314-323.

14. Radaković R, Đurović Ž, Prosinečki R, Vulović R, Peulić A, Nikolić D, et al. Opšti parametri Tracking motion analize igrača FK Crvena Zvezda tokom utakmice 4. Kola kvalifikacija za Ligu Evrope 2012./13. In International Conference Faculty of Sport and Physical Education; 2013; Belgrade.

15. Carling C, Bloomfield J, Nelson L, Reilly T. The role of motion

analysis in elite soccer: contemporary performance measurement techniques and work rate data. Sports Medicine. 2012; 38(10): 389.

## Tables

Table 1. Descriptive statistics of the whole dataset for morphological variables

| | Mean | SD | cV% | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| BH (cm) | 182.61 | 5.791 | 11.34 | 0.344 | 0.399 | 171 | 198 |
| BW (kg) | 77.33 | 6.775 | 33.53 | -0.256 | -0.141 | 62 | 91 |
| BMI (kg•m$^2$) | 22.831 | 2.852 | 45.90 | -5.832 | 1.674 | 19.2 | 25.5 |
| BFM (%) | 9.098 | 2.492 | 8.14 | -0.359 | -0.621 | 3.7 | 14.1 |
| BMM (%) | 43.294 | 1.750 | 6.21 | -0.132 | -0.870 | 40.1 | 46.5 |

Table 2. Descriptive statistics of the whole dataset for motor abilities variables

| | Mean | SD | cV% | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| V10mWOB (s) | 1.617 | 0.087 | 53.81 | -0.084 | -0.726 | 1.45 | 1.81 |
| V20mWOB (s) | 2.915 | 0.121 | 4.14 | 0.184 | -0.791 | 2.71 | 3.20 |
| V30mWOB (s) | 4.050 | 0.164 | 4.09 | 0.415 | 0.019 | 3.77 | 4.49 |
| ZZWOB (s) | 6.856 | 0.598 | 8.75 | -0.434 | -1.487 | 5.79 | 7.60 |
| ZZWB (s) | 8.417 | 0.886 | 10.51 | -0.172 | -0.871 | 6.93 | 10.18 |
| AI10/20m | .554 | 0.025 | 4.58 | 0.017 | -0.700 | 0.504 | 0.604 |
| AI10/30m | 0.400 | 0.023 | 5.73 | 0.098 | 2.540 | 0.358 | 0.491 |
| IBCS | .817 | 0.043 | 5.29 | -0.273 | -0.227 | 0.711 | 0.915 |
| JWOS (cm) | 42.363 | 5.131 | 12.52 | -0.924 | 2.947 | 21.5 | 51.4 |
| JWS (cm) | 52.814 | 6.944 | 5.37 | 0.534 | -0.276 | 41.1 | 70.2 |
| RJ (cm) | 37.464 | 3.123 | 4.12 | 0.203 | 0.781 | 29.9 | 45.0 |

Table 3. Descriptive statistics of the whole dataset for competition performance variables

| | Mean | SD | cV% | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| TD (m) | 10597.25 | 1061.617 | 10.03 | 0.184 | -0.572 | 8429.52 | 12602.24 |
| TDW (m) | 4550.55 | 410.46 | 9.02 | -0.816 | 1.026 | 3301.36 | 5243.99 |
| TDLI (m) | 4047.45 | 765.83 | 18.94 | 0.442 | -0.179 | 2675.95 | 5850.53 |
| TDAT (m) | 922.05 | 262.49 | 28.41 | -0.039 | -1.191 | 471.36 | 1393.53 |
| TDVO2max (m) | 584.93 | 159.42 | 27.23 | 0.419 | -0.038 | 288.77 | 994.25 |
| TDMI (m) | 474.14 | 166.73 | 35.14 | 1.537 | 4.221 | 220.52 | 1134.03 |
| %EM (%) | 18.51 | 3.375 | 18.23 | -0.057 | 0.960 | 10.532 | 28.060 |
| HIEPM | 38230.32 | 15896.04 | 41.61 | 0.894 | 2.341 | 10328.7 | 96614.7 |

Table 4. ANOVA test results for the best multiple regression model predicting total distance covered

| ANOVA | | | | | |
|---|---|---|---|---|---|
| | Sum of Squares | df | Mean Square | F | Sig. |
| Regression | 1.927E+07 | 7 | 2.752E+06 | 5.206 | 0.001[e] |
| Residual | 1.216E+07 | 23 | 528627.195 | | |
| Total | 3.142E+07 | 30 | | | |

Table 5. Coefficients of the best multiple regression model predicting total distance covered

| Variables | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | -85299.761 | 97424.469 | | -0.876 | 0.390 |
| ACC10mWOB | -134802.741 | 41232.768 | -11.783 | -3.269 | 0.003 |
| ACC20mWOB | 68788.374 | 22524.741 | 7.100 | 3.054 | 0.006 |
| ACC30mWOB | 5934.091 | 1423.058 | .791 | 4.170 | 0.000 |
| ZZWOB | 18705.324 | 7908.605 | 4.199 | 2.365 | 0.027 |
| ZZWB | -14664.566 | 6426.008 | -6.311 | -2.282 | 0.032 |
| AI10/20m | 371321.180 | 116947.656 | 7.818 | 3.175 | 0.004 |
| IBCS | -147998.968 | 73531.927 | -5.690 | -2.013 | 0.056 |

Table 6. ANOVA test results for the best multiple regression model predicting HIEPM

| ANOVA | | | | | |
|---|---|---|---|---|---|
| | Sum of Squares | df | Mean Square | F | Sig. |
| Regression | 5.593E+09 | 8 | 6.991E+08 | 4.133 | 0.004[d] |
| Residual | 3.722E+09 | 22 | 1.692E+08 | | |
| Total | 9.315E+09 | 30 | | | |

Table 7. Coefficients of the best multiple regression model predicting HIEPM

| Variables | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | -2538484.785 | 1040926.479 | | -2.439 | 0.003 |
| ACC10mWOB | -1829736.711 | 646990.821 | -9.290 | -2.828 | 0.010 |
| ACC20mWOB | 952131.409 | 363611.397 | 5.708 | 2.619 | 0.006 |
| ZZWOB | 20869.575 | 14865.075 | 0.272 | 1.404 | 0.004 |
| ZZWB | -12647.660 | 7035.325 | -0.316 | -1.798 | 0.005 |
| AI10/20m | 5097935.849 | 1837051.275 | 6.234 | 2.775 | 0.001 |
| JWOS | -1827.259 | 860.341 | -0.433 | -2.124 | 0.005 |
| JWS | 1015.313 | 725.801 | 0.321 | 1.399 | 0.006 |
| RJ | -2096.295 | 1138.419 | -0.375 | -1.841 | 0.009 |

Table 8. ANOVA test results for the best multiple regression model predicting %EM

| ANOVA | | | | | |
|---|---|---|---|---|---|
| | Sum of Squares | df | Mean Square | F | Sig. |
| Regression | 5255134.204 | 6 | 875855.701 | 5.313 | 0.001[f] |
| Residual | 3956641.078 | 24 | 164860.045 | | |
| Total | 9211775.282 | 30 | | | |

Table 9. Coefficients of the best multiple regression model predicting %EM

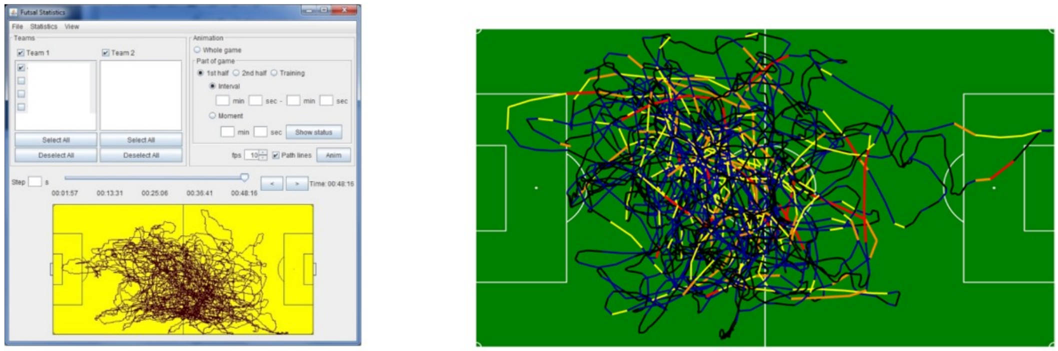
| Variables | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | -86646.093 | 32490.927 | | -2.667 | 0.013 |
| ACC10mWOB | -63079.109 | 20178.801 | -10.184 | -3.126 | 0.005 |
| ACC20mWOB | 32863.598 | 11346.369 | 6.265 | 2.896 | 0.008 |
| ZZWOB | 827.301 | 407.305 | 0.343 | 2.031 | 0.053 |
| ZZWB | -623.345 | 205.856 | -0.496 | -3.028 | 0.006 |
| AI10/20m | 174706.273 | 57190.224 | 6.794 | 3.055 | 0.005 |
| JWOS | -56.615 | 18.528 | -0.427 | -3.056 | 0.005 |

## Figure captions

Fig. 1: Interface for BioIRC Tracking Motion software system (a); Total trajectory of a single player during a halftime with different classifications based on movement intensity (b)

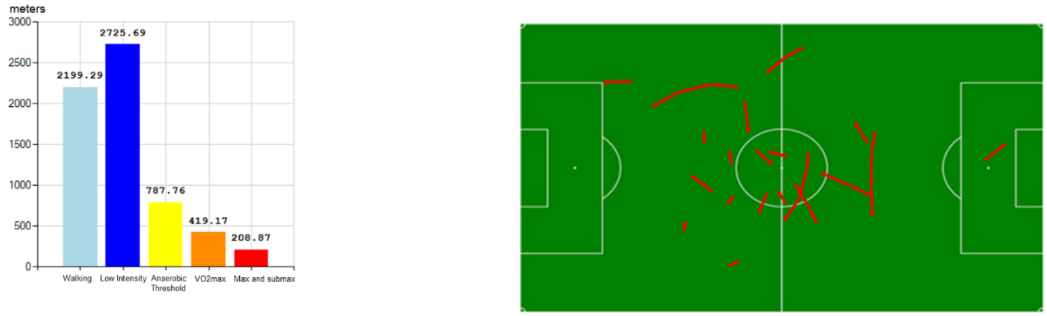
Fig. 2: Quantitative measurements of player's movement intensity during a halftime (a); The player's movements performed with the high intensity (b)

# Figures




a b

Fig. 1


meters
3000
2500
2000
1500
1000
500
0
2199.29
2725.69
787.76
419.17
208.87
Walking
Low Intensity
Anaerobic Threshold
VO2max
Max and submax

a

b

Fig. 2