Application Of An Integrated Metabolic Power Paradigm In Elite Soccer

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Abstract

The aims of this thesis were to: 1) to assess whether different frequencies of GPS systems can influence the measure of distance while accounting for different speeds; 2) to determine the differences in energy cost of straight (C_r)- and shuttle-running (C_{sh}) in soccer players vs. marathoner runners by applying di Prampero's approach; 3) to assess energy cost of straight-running (C_r) in elite professional soccer players in their ecological setting and determine whether changes in C_r can be established; 4) to investigate the average metabolic power (MP) on a soccer-specific test through direct (K4b^2, $P_{\dot{V}O2}$) and indirect (GPS, P_{GPS}) measurement of O_2 consumption by di Prampero's approach and modifying Minetti's equation of C; 5) to investigate how different systems of play effect soccer outcomes with special attention to high-intensity; 6) to evaluate the existence of significant correlations between physical and physiological performance data on elite soccer database of matches and training sessions.

When reviewing the literature, it became apparent that smaller and smaller margins determine the outcome of a game. As a result, highly scientific processes are being developed to help players, managers and sport scientists gain an understanding and advantage in soccer. Through time-motion analysis it has been observed that players perform a multitude of physical activities, that consist of sprinting, turning, stopping and jumping, and the amount of time spent during these actions. Since the introduction of GPS, there has been a rapid uptake of GPS technology within soccer and numerous studies have examined the validity and accuracy of GPS systems to establish the accuracy of measuring physical data. Although faster GPS systems have been validated for team sports, some doubts continue to exist on the validity and accuracy of these.

To address this problem, a pilot study was performed to assess the validity of GPS technology using a laser speed gun by tracking the movement of the ten participants. The GPS system with an increased sample frequency (rate) provided valid means of assessing

running speed during rapid acceleration and deceleration that occur during linear runs and runs with tight changes of direction using a 100-Hz laser system.

To gain a better understanding about the sport specific demands of soccer, it is important that we establish the determination of energy cost (C) using a valid method. A second pilot study was performed to address this issue and compare C of straight- and shuttle-running in 10 professional soccer players *vs*. 7 marathoner runners. It was found that straight-running energy cost (C_r) is significantly greater in soccer players, while shuttle running was significantly lower. Therefore, the specificity of the sport plays a major role on the energy cost required for the specific movements required to excel in the given sport.

Once the C was established, it appeared that the need to monitor and possibly condition the C_r in soccer players was advisable. Therefore, an up-to-date assessment of C_r in elite professional soccer players in their ecological setting was provided to see whether changes in C_r are different compared to values established previously in literature. A total of seventeen professional players were involved in this study and performed a straight-running energy cost assessment on a UEFA standard grass soccer pitch. From the acquired data, C_r was calculated and compared to previous research. It was found that the C_r of straight-running on a UEFA standard grass soccer pitch is 4.66 $J \cdot kg^{-1} \cdot m^{-1}$ in elite professional soccer players which is different to previous observations. This study provided an up-to-date measure of on-pitch C_r and was employed in the subsequent studies.

To truly gain an understanding of the amount of effort during soccer performance it is important to understand and incorporate the concept of di Prampero and Osgnach in relation to energy cost and metabolic power. As a result, a new energetic model for soccer, considering acceleration and deceleration, based on the previous theories of di Prampero *et al*. (2005) and Minetti *et al*. (2002). This study looked to establish the average MP of a specific soccer test through direct and indirect measurements of oxygen consumption using di Prampero’s approach while modifying Minetti’s equation of energy cost by testing 13 professional soccer players. The new energy cost equation calculation was derived from findings in the previous study and it was established that metabolic power was slightly underestimated as a result.

Once C_r and MP were established, our next study assessed whether specific variables and different formations in soccer can predict performance outcome. What are the differences between the 1st and 2nd half and between formations and what specific variables influence the outcome of results when assessing a team over the course of 19 home games? A decrease in both physical performance (i.e., TDC) and metabolic power (MP) variables are present with almost all formations in the second half. When winning significantly longer distances and distances by speeds more than 16 $km \cdot h^{-1}$ were covered when compared to losing. Most of the successful teams showed better technical skills variables values than the less successful ones.

The selection of the appropriate tactic plays an essential role during every pre-game preparation phase, to ultimately win the game, but little research has been conducted. Therefore, the final study investigated the correlation between the essential parameters analysed during training sessions and during official matches of elite soccer, as well as investigating the ‘functional model’ proposed in training. There were positive correlations between the performance data analysed during the games played in training and locomotor data obtained through video match analysis.

Dedication

To my mentors and friends.

Thank you for all your support along the way.

YNWA.

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I have thoroughly enjoyed my time over the last seven years and met many people who contributed to these studies. I would like to take this opportunity to thank all those individuals, which I am now massively indebted to, who have inspired me, supported me and helped me with the process of data collection and analysis. Special thanks must go to all the soccer clubs with which I have also collaborated indirectly (A.S. Roma, Calcio Catania, A.C.F. Fiorentina, U.C. Sampdoria, A.C. Milan, Sevilla F.C. and Club Italia of F.I.G.C.), and which motivated me in the beginning to move to the UK, where Tom Reilly's echo and his effort to make the understanding of this sport even more scientific, had the maximum impulse.

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Glossary of Terms

[La-]b	Blood lactate concentration [$mmol \cdot L^{-1}$]
Δ	Delta/change
©	Copyright symbol
®	Registered trademark symbol
a_{max}	Maximal voluntary acceleration
Aer	Aerobic contribution
AnAl	Anaerobic Alactic
AnL	Anaerobic Lactic
ANOVA	Analysis of Variance
ATP	Adenosine Triphosphate
C	Energy Cost [$J \cdot kg^{-1} \cdot m^{-1}$]
CBT	Computer Based Training
CI	Confidence Interval
CO_2	Carbon Dioxide
CoD	Change of Direction
CP	Creatine Phosphate
C_r	Energy Cost of straight-running
C_{sh}	Energy Cost of shuttle-run
C_w	Energy Cost of walking
ED	Equivalent Distance
EDI	Equivalent Distance Index, ratio between ED and TD
EE	Energy Expenditure [$kJ \cdot kg^{-1}$ or $kcal \cdot kg^{-1}$]
EEE	Estimated Energy Expenditure
EGNOS	European Geostationary Navigation Overlay Service
EM	Equivalent Mass
EPTS	Electronic Performance and Tracking Systems
ES	Equivalent Slope
FIFA	The Fédération Internationale de Football Association
GPS	Global Positioning System
HDOP	Horizontal Dilution of Precision
HR	Heart Rate [$beats \cdot min^{-1}$]
HR_{max}	Maximum Heart Rate
IQR	Interquartile Range
KT	Grassy terrain constant
LoA	Limits of Agreement
LPM	Local Position Measurement
LPS	Local Positioning System
MAV	Maximal Aerobic Velocity
MP	Metabolic Power [$W \cdot kg^{-1}$]
MSRT	Multistage 20-m Shuttle Run Test
MST	Multistage Test
N_2	Balance Nitrogen
NSAT	Number of Satellites

O_2	Oxygen
PEI	Physical Efficiency Index
P_{GPS}	Metabolic Power estimated from locomotor demands
$P_{\dot{V}O2}$	Metabolic Power calculated using net $\dot{V}O_2$ responses and traditional calorimetry principles
RER	Respiratory Exchange Ratio
RPE	Rating of Perceived Exertion
RSA	Repeated Sprint Ability
SEE	Standard Error of Estimates
SPSS	Statistical Package for Social Science
SSG	Small-Sided Games
TEI	Technical Efficiency Index
TDC	Total Distance Covered [m or km]
TL	Training Load
™	Unregistered trademark symbol
TMA	Time-Motion Analysis
TP	Total High Power
TS	Total High Speed
TUM	Technical University of Munich
UEFA	Union of European Soccer Associations
v	Speed [$m \cdot s^{-1}$ or $km \cdot h^{-1}$]
v_{init}	Initial running speed
VID	Video Technology
VMA	Video Match Analysis
$\dot{V}O_2$	Oxygen Uptake [$mL \cdot min^{-1} \cdot kg^{-1}$]
$\dot{V}O_{2max}$	Maximal Oxygen Consumption [$L \cdot min^{-1}$]
$\dot{V}O_{2n}$	Net $\dot{V}O_2$, above its resting value
WAAS	Wide Area Augmentation System
χ^2	Chi-squared

Chapter 1: General introduction

1.1: Background

Results in the modern era of sports are often determined by the smallest of margins. The difference between success and failure can be quantified in the smallest of increments (Drust *et al.*, 2005). Decisions made by an individual or a team can result in winning a medal, scoring or conceding a goal and ultimately lead to defeat or victory respectively (Casanova *et al.*, 2013). In soccer, the 2011/2012 Barclays Premier League campaign saw Manchester City and Manchester United go into the final game of the season level on points, though Manchester City had the superior goal difference by eight. Manchester City were 2-1 down at home against the 10 men of Queens Park Rangers Soccer Club, when five minutes of added time were added. Manchester City Soccer Club take a 3-2 victory over Queens Park Rangers Soccer Club with two goals scored in added time to win the league title on goal difference over their arch rivals Manchester United. Due to the ever-increasing importance of narrow margins and athletic development play in successful sporting achievement, highly scientific processes are being developed to aid players, managers and sport scientists analyse performance in sport (Bourdon *et al.*, 2017; Drust *et al.*, 2007).

Sport performance is highly dependent on a myriad of factors with sports scientists continuously striving to assist athletes and coaches to achieve their ultimate sporting performance, through applying knowledge and techniques from areas ranging from physiology, coaching science, biomechanics and psychology (Girard *et al.*, 2009; Stølen *et al*., 2005). Success in soccer is directly associated with skill proficiency in addition to physiological, tactical and cognitive capabilities (Casanova *et al.*, 2013). Through time-motion analysis, it has been found that soccer players are requested to perform a multitude of physical activities, consisting of sprinting, turning, stopping and jumping (Di Salvo *et al.*, 2007; Iaia *et al.*, 2009; Nakamura *et al.*, 2017). Soccer is a high-intensity intermittent sport, which imposes high physical demands on players (Bangsbo, 2006; Reilly, 1997). Research has reported soccer players cover approximately a total distance (TDC) of 10 km during a match (Di Salvo *et al*., 2007; Mohr *et al*., 2003). Approximately 30 to 60% of the time is spent at a low-intensity, such as walking, jogging, or low/moderate speed running. High intensity actions such as high-speed runs (> 19.1 $km \cdot h^{-1}$) and sprints (> 23 $km \cdot h^{-1}$), make up 6% and 4% of TDC, respectively (Di Salvo *et al*., 2007; Gregson *et al*., 2010). Further, soccer matches have shown to elicit over 70% of maximum oxygen consumption ($\dot{V}O_{2max}$), emphasising the need of a high aerobic capacity (Bangsbo *et al*., 2006; Reilly, 1997). Although soccer is characterised by activities mostly relying on the aerobic energy pathways, high values of blood lactate [La-]b (2-14 $mmol \cdot L^{-1}$) observed during matches highlight the need of intermittent contributions from anaerobic energy sources (Bangsbo, 2006; Krustrup *et al*., 2006; Santos-Silva *et al.,* 2017). Therefore, it has been found that soccer places high physiological demands on the soccer player and a well-developed aerobic and anaerobic capacity is required in order to excel and cope with the demands of the sport throughout an entire season (Evaggelos *et al.*, 2012; Kalapotharakos *et al*., 2011; Thorpe *et al.*, 2015).

To manage the high physical demands of training and match play as well as scheduling recovery, monitoring training load plays a crucial role inducing sport specific adaptation and helping with injury prevention strategies (Impellizzeri *et al*., 2004; Rogalski *et al*., 2013; Thornton *et al*., 2016). A large variety of physiological variables, such as heart rate (HR), oxygen consumption ($\dot{V}O_2$), blood lactate [La-]b concentration, sessional rates of perceived exertion (RPE), have been used to assess the physiological demands observed during matches and training to help determine exercise intensity (Alexandre *et al*., 2012; Achten & Jeukendrup, 2003; Castellano *et al*., 2015; Coutts *et al*., 2009; Gaudino *et al.*, 2015; Impellizzeri *et al*., 2005). It is important that the physiological markers related to players characteristics which are being analysed are accurate and useful. Although these variables have shown to be useful, they present a significant number of limitations as soccer performance is affected by other factors such as environmental, technical and tactical aspects (Casamichana *et al*., 2013; Manzi *et al*., 2014). Recently, critical match analysis methods widely used in soccer have included the application of the video-based time-motion analysis. and the use of semi-automatic cameras, the Global Positioning Systems (GPS). Through these systems, sport scientists and coaches have been able to continuously collect data related to match play and training player performance to better understand the nature and interaction between these factors (Bastida Castillo *et al.,* 2018).

Global Positioning Systems (GPS) allow users to accurately determine positions on the surface of the earth from a network of satellites orbiting around the planet. Initially designed and developed for military use only, GPS is now used in a multitude fields, and a major game changer in sport (Bastida Castillo *et al.,* 2018; Steede-Terry, 2000). In the last few years, there has been a rapid uptake of GPS technology within soccer to track speed of movement and distance covered during training sessions and match play (Aughey, 2011; Bastida Castillo *et al.,* 2018). Several studies have examined the validity and reliability of GPS systems to establish the accuracy of measuring physical data. It must be noted that these measurements have been determined predominately during steady-state movements, using devices with a low rate of GPS sampling frequency, i.e. one measure every second. Although high frequency GPS systems (5-Hz and 10-Hz) have been validated for team sports, some doubts continue to exist on the validity and reliability of GPS in measuring short high-velocity linear running (> 20-30 $km \cdot h^{-1}$) and side to side movements, which are typical actions in soccer (Bastida Castillo *et al.,* 2018; Coutts *et al*., 2010; Padulo *et al.,* 2019). Since the ability to quickly accelerate, decelerate and change direction at several ranges of speed and distance is critical to performance in soccer (Reilly, 2004). The use of GPS/video analysis system with higher sampling frequencies would be advantageous to aid with the analysis of high intensity sprinting activities during matches (Felipe *et al.,* 2019; Linke *et al.,* 2018; Pons *et al.,* 2019).

Physical capacity assessed via the Yo-Yo intermittent recovery test (Krustrup *et al.,* 2003; 2005) and playing positions (Bradley *et al*., 2010; Di Salvo *et al*., 2009, Chmura *et al.,* 2018), have been to be closely related to the TDC through high-intensity running in soccer matches (Bradley *et al*., 2009). Through the application of GPS practitioners can generate further information regarding these physical differences and play a major role in devising specific training programmes for each playing position (Di Salvo *et al*., 2009; 2013; Svensson & Drust, 2005). However, it is important to not only focus on high intensity runs but also the ability to quickly accelerate, decelerate and change direction at several ranges of speed and distance; factors that are critical to performance (Reilly, 2004; Tang *et al.,* 2018). Further, in order to gain a better understanding surrounding the load and fatigue during soccer performance incorporating the concept of Osgnach *et al.* (2010) and di Prampero (2005) regarding energy cost and metabolic power is vital. Assessment of instantaneous metabolic power based on actual metabolic power also taking into account accelerations and decelerations during the various phases of the match and will provide in-depth information surrounding the concept of "high intensity" in intermittent soccer activity (Osgnach *et al*., 2010).

Defining the physical demand of soccer games is crucial to schedule appropriate training and recovery periods and thus maximise performance (Bowen *et al.,* 2016; Impellizzeri *et al*., 2004). Only measuring energetic demand through external load assessment fails to estimate the actual energetic demand according to each player, not taking into account the stress opposed on each individual player. Using only external metrics such as TDC and velocity of a specific movement, fails to characterise the authentic physiological response of the actual task executed (Osgnach *et al*., 2010). Because of this, Osgnach *et al*. (2010), proposed a new energetic model for soccer, considering acceleration and deceleration, based on the theory of di Prampero *et al*. (2005) and Minetti *et al*. (2002). In brief, this new model has been established upon the theory of the "equivalent slope" (ES), by establishing that accelerated running on a flat terrain, is mechanically equivalent to running on the uphill at a constant speed, where the rate of acceleration determines the angle of the slope.

Minetti *et al.,* (2002), was able to determine the energy cost of running uphill over a range of gradients (%). This knowledge can then be used to estimate the energy cost of accelerations and decelerations with the relationship between the energy cost of constant-speed running and terrain's slope (di Prampero *et al*., 2005; Minetti *et al.,* 2002; Osgnach *et al.,* 2010). Osgnach's *et al.*, (2010) approach provides a comprehensive means estimating total and instantaneous metabolic demands with the combination of running speed and acceleration/deceleration level. The energy cost (C) of soccer match play estimated from this approach was found to be 2-3 times higher than C calculated when using the previous methods, which only considered speed and TDC (Osgnach *et al*., 2010). Consequently, this method allows coaches to have an accurate estimate of the metabolic demand during soccer-related activities. Furthermore, it could be useful to help determine the actual internal/external load during training (Delaney *et al.,* 2018; Osgnach *et al*., 2010; Oxendale *et al.,* 2017). Limited data is available regarding the actual C and C_r changes in elite soccer players, although there are preliminary indications that elite youth soccer players C_r displays changes over the course of a season (Buglione & di Prampero, 2012). It appears advisable to monitor and possibly condition the C_r in soccer players however such a proposition would need to be predicated up the need to more fully understand the C in elite professional soccer players in their soccer specific settings of match play and training.

In determining C_r is important to understand several factors influence the accuracy of the C_r estimation. The original concept involved in C_r estimation was based on running on compact terrain, i.e. treadmill (di Prampero *et al*., 2005; Minetti *et al*., 2002). However, it has been established that movement across a grass surface elevates C_r by ~30% when compared to running on dense terrain (Pinnington & Dawson, 2001). Taking into consideration that 'The Fédération Internationale de Football Association" (FIFA) has stipulated that competitive games be played on FIFA standardised artificial turf soccer pitches (https://football-technology.fifa.com/media/1230/artificial_turf_recycling.pdf, accessed 22 July 2019), it is important to gain further understanding how artificial pitches affect the determination of C_r. Only a few studies have considered C_r differences between natural (grass) and synthetic surfaces and found there to be minimal differences (Hughes *et al*., 2013; Sassi *et al*., 2011). Numerous factors have been found to potentially influence C_r of running. Fitness level is a factor that has been found to possibly influence C_r as running economy can be improved through training (Beneke & Hütler, 2005; Iaia *et al*., 2009). Research on youth professional soccer players showed that C_r of running increased by 14% from pre-season to in-season (Buglione & di Prampero, 2012). Taking into account such limitations, Osgnach *et al*. (2010) based their C equation on the work conducted by Minetti *et al*. (2002), while adding a correction for surface characteristics based upon the work of Pinnington and Dawson (2001), which consists of a multiplication term of 1.29 (KT = 1.29) which is considered the difference between running on a treadmill and a grass surface. However, the incorporation of this multiplication term into Osgnach's model presents a critical issue that may impact the accurate determination of the energy cost of soccer-specific activities. Pinnington and

Dawson (2001) correction model was based upon a recreational runner population who may not present a suitable kinematic model of elite soccer players, due to differences in muscle fibre types, fibre recruitment patterns and concomitant metabolic adaptations in energy systems pathways (Lorenz *et al.,* 2013). Therefore, the coefficient of multiplication (KT) may not provide an accurate representation of the metabolic constant in elite soccer players. Consequently, the C_r equation proposed by Osgnach *et al*. (2010), may fail to reflect the energy cost imposed by movement on a grass surface in elite soccer players. Consequently, estimation of the metabolic power in elite soccer players using the Osgnach' equation could be impaired.

During soccer match play, training simulation and small sided games, rapid acceleration, deceleration and multi-directional movements are significant features of performance (Terje *et al.*, 2016). The equation presented by Minetti *et al.* (2002) upon which Osgnach's *et al.* (2010) model is founded does not reflect the 'real C_r' of accelerations and decelerations, since the algorithm only considers movement in the variations of speed between +4.5 $m \cdot s^{-2}$ and -4.5 $m \cdot s^{-2}$. The equation does not provide an accurate estimation of energy cost in the case where running speed exceed this range; particularly during decelerations movements with high eccentric components. Because of this, Osgnach *et al*. (2010) suggested that greater rates of deceleration needed to be considered (-4 $m \cdot s^{-2}$ to -6 $m \cdot s^{-2}$). In this context of the energetics of accelerated and decelerated running using instantaneous metabolic power in soccer several contrary opinions as to the application, efficacy and usefulness of the metabolic power paradigm have been advanced (Buchheit *et al.*, 2015a). More recently, di Prampero *et al*. (2018) has advanced new modifications of his energy cost model with substitution of the energy cost of running at constant speed (C_r) with the C of race walking (C_w). However, this may still create an underestimation of metabolic power in non-walking phases, therefore the use 'old' equation of Minetti *et* *al*. (2002) further modified to reflect these issues may provide more realistic estimations of metabolic power. The metabolic power paradigm which is increasingly applied in elite soccer training and preparation still utilises the original algorithm embedded in the current software models. Despite this, the utility of the metabolic power approach has gained traction with applied practitioners in the applied settings (Coutts *et al.,* 2015; Kempton *et al.,* 2015; Polglaze *et al.,* 2018). Recently, Martín García *et al*. (2018) have begun to quantify the microcycle structure and load of the weekly elite soccer training along with match play data, to systematically manage the training and facilitate compensatory training for players without game time (Gaudino *et al.,* 2014; Hoppe *et al.,* 2017). Further to these others have implemented such a model into the applied practice with elite clubs throughout Europe.

Increasingly the analysis of physical data through these models is being viewed in the context of its use as a metric related to the technical-tactical context of match play. The tactical dimension of match-play is likely to hierarchically imposes these the physical response these metrics monitor. As such a clearer understanding of the technical and tactical implications must be considered more fully which may offer information about the efficiency of a playing position in the field or an ideal system of tactical system of play when facing specific opponents or when adopting chosen game-philosophy.

1.2: Statement of the problem

Considering the issues outlined in the previous section. In the first instance this thesis is concerned with establishing whether GPS enables the assessment of metabolic power in soccer by determining the energy cost of straight (C_r)- and shuttle-running (C_{sh}) in elite soccer players and see whether changes can be observed in these parameters under different play specific scenarios pitch conditions and movement patterns. Secondly, it is concerned with examining the efficacy of a new metabolic modified metabolic power algorithm incorporating the point raised in point 1 relative to the existent model. Finally, it aims is to determine external training load analysis and physical match performance under different technical and tactical regime in elite soccer.

1.2.1: Aims

Aim of thesis.

The aim of this thesis is to develop, validate and apply a new model of metabolic power determination in an elite soccer model.

Summary of the aims of this thesis are:

1. The first aim is to assess and validate different frequencies of GPS systems when measuring elite soccer performance metrics and determining the energy cost of straight (C_r)- and shuttle-running (C_{sh}) in soccer specific adapted *vs.* non-adapted high fitness individuals applying di Prampero's *et al*. (2005) approach (pilot works).

   The second aim is to then determine the energy cost of straight-running (C_r) in elite professional soccer players following a soccer specific movement scenario. (Chapter 3).

2. To perform a calibration investigation on metabolic power (MP) on a soccer-specific test through direct (K4b^2, $P_{\dot{V}O2}$) and indirect (GPS, P_{GPS}) measurement of oxygen consumption by di Prampero's approach (2005) and using a newly modified model of Minetti's equation of C. (Chapter 4).

3. To investigate the tactical system of play effects on the outcome of a soccer match with special attention to high intensity. (Chapter 5).

4. To evaluate associations between physical and physiological performance data on elite soccer database of matches and training sessions. (Chapter 6).

1.2.2: Objectives

Realisation of the aims will be achieved through several objectives listed below:

1. Aim 1: Objective: To use new technologies applied on soccer for understanding the accuracy of GPS systems useful for training and match load investigation, by validating a high-frequency GPS in a soccer-specific circuit analysing the total distance covered and its accuracy in different types of sprint activities with acceleration and deceleration phases, achieved through pilot study 1.

   Aim 2: Objective: To determine the effects of elite population specific adaptation in energy cost of movement via comparison of constant speed linear-running and shuttle running in elite marathon runners and elite soccer players to highlight sport specific adaptations. This will be achieved through pilot study 2.

   Aim 3: Objective: Following the validation of GPS and a sport-specific circuit the new specific energy cost (C_r) of movement in elite soccer players will be determined on a UEFA grass pitch by applying the value expressed in $J \cdot kg^{-1} \cdot m^{-1}$ as a new constant term in Minetti's *et al*. (2002) equation. This will be achieved through study 1 using the relevant findings from pilot studies 1 and 2. (Chapter 3).

2. Aim 4: Objective: Validation of the new energy cost equation (Aim 3) during soccer-specific movement protocols through comparison of directly measured energy expenditure ($P_{\dot{V}O2}$) to values determined indirectly through GPS (P_{GPS}, metabolic power from GPS). This will be achieved through study 2. (Chapter 4).

3. Aim 5: Apply the new metabolic power algorithm (Aim 4) to elite soccer data for studying physical data (e.g. variations of speed, metabolic power *etc*.) in a technical-tactical context (system of play). Further, a longitudinal view of a team was established, through comparing performance and results over the course of a season of home matches. This will be achieved through study 3 (Chapter 5).

4. Aim 6: Objective: Examine associations between physiological performance data through 5 months of training sessions and matches of an elite professional soccer club. This will be achieved through study 4 (Chapter 6).

Chapter 2: Literature review

2.1: Structure of the review

The purpose of the literature review is to outline the scope and influence of match analysis methods in soccer. It is not the intention to be a comprehensive review of match/performance analysis approaches in soccer but rather a review to familiarise the reader with the basic framework of match-analysis, with reference to GPS. It is also the aim to provide a firm context regarding the assessment of metabolic power in soccer by determining the energy cost (C). Further, it will establish whether previous equations utilised to assess this concept are appropriate and determine a whether an association between training load analysis and physical match performance variables in elite soccer exist.

The review begins with an introduction of the scientific methods, research, and technologies in soccer; after which match analysis methods are explained. A comprehensive account of the application of video match analysis is then provided, with a more detailed section on the application of GPS in field sports and its future application. The review will then aim to define how metabolic power can be analysed and integrated within sport.

2.2: Basic introduction

The professional sports industry has started to adopt the use of more scientific methods, research, and technologies in their approaches so that they can be more productive by providing quantification of the physical demands in soccer (Molinos, 2013). It is safe to say that the performances in sports are affected by the technical and tactical aspects while also being affected by mental and physical agility . Failure to have all these aspects makes the soccer player less effective (Paul *et al.*, 2015).

Over the past few years, coaches have used GPS devises to analyse the characteristics of players. Coaches of soccer teams are continuously trying to codify the performances of the players to help to quantify the microcycle structure and load of the weekly elite soccer training along with match play data (Gaudino *et al.*, 2014; Hoppe *et al.*, 2017). While primary data such as the total distance covered (TDC), and average speeds are easily captured in the past, a comparison of two or more players has been difficult (Di Salvo *et al.*, 2006). Therefore, new technologies such as GPS have enabled coaches to accurately estimate high quality and accurate metrics of player performance and estimate markers of both internal and external physical and physiological loads applied using different models systems (Buchheit *et al.*, 2014; Hoppe *et al.*, 2018; Randers *et al.*, 2010). Further, the use of video analysis is also used by the media to give viewers a series of statistics that articulate players work rate (Halvorsen *et al.*, 2013).

2.3: Match Analysis methods

The main match analysis methods which are commonly used in numerous sports are the application of video-based time-motion analysis (TMA), the use of semi-automatic cameras and global positioning systems (GPS). Video-based TMA has been widely applied and provided evidence that distance which players cover at high intensity are highly dependent on playing position, capacity, performances of a player, and the standard of competition (Buchheit *et al.,* 2014; Hoppe *et al.,* 2018; Randers *et al.,* 2010). It has also been established that player work rate and intensity usually decrease after the first minutes of high-intensity periods and during the end of the match because of fatigue (Drust *et al.,* 2007). Fatigue occurs because of the high-intensity levels at the start of the first and second halves and towards the end of the first and second halves (Mohr *et al.,* 2005). With the new technical advancements, this has led to the creation of new approaches through which the movement patterns of soccer players can be examined more efficiently and more effectively. Through these new approaches a more comprehensive study of locomotion patterns in football are being established (Randers *et al.,* 2010). These investigations allow for more meaningful performance parameters being established and provide a framework to design training in accordance to individual player needs (Hoppe *et al.,* 2018).

2.4: The application of Video Match Analysis (VMA)

Time-motion analysis (TMA) has been studied extensively applied in soccer, through many different methodological approaches. Brown *et al*. (2016) examined the exclusion of breaks in the analysis of plays during a 110-minute game. Buchheit *et al*. (2015a) and Gaudino *et al*. (2014) followed a similar approach, although they analysed a 90-minute game and a 30-minute game, respectively. All these authors conducted their analysis throughout the entire game but failed to indicate whether their investigation was performed based on a 90-min match including over time and injury time in their studies or not. Incorporating over time or injury time would not only yield different results but would also provide more specific and accurate overall findings. However, a plethora of studies have analysed the entire duration of the game including both extra and over time by excluding the half-time breaks; Walker *et al*. (2016) examined a football game for 95 minutes with differences observed in several essential physiological variables when they compared the whole duration of a match including breaks in play (match time) and the duration of the match only when the ball is in play (clock time). Increases in the total duration and frequencies of locomotors activities and the total distances covered. In addition, the authors also noticed a significant difference in the individual locomotors' activity patterns when clock time and match time are compared (Barbero-Alvarez *et al.*, 2008). According to Witte and Wilson (2004), it was found that there is an 11% increase between the match-time and clock time with a 4.4% decrease in running, a 0.49% decrease in sprinting sideways, and a 4.6% decrease in rushing backward. Osgnach *et al*. (2010) showed that 74% of all match-time distances could be classified as low-intensity activities. McMillan *et al*. (2005) and Chmura *et al.* (2018) also reported that the majority of the match time data consisted of low-intensity activities. Reports suggest an increase of 695 meters ditance covered was observed when analysing match-time distances from clock-time distance in low-intensity games however in high-intensity games this ddistance covered further increases. It can be noted that highly intense activities occure more frequently when assessing clock-time data, due to the break and overtimes incorporated in match-time data. It has been found that during situations where the ball is not in play, players tend to walk and slow the pace of the game so that they can recover and maximise their opportunities during the game (Walker *et al*., 2016), thus increasing time spent on low-intensity activities (Cummins *et al.*, 2016). Closer analysis has found differences in work to rest ratios of 1:4:1 when looking at clock time and 7:4:1 when only assessing match time. It is therefore appropriate to understand the differences in results of work to rest ratios obtained between match time and clock time, with a failure to understand both concepts resulting in a misrepresentation of game analysis findings. The importance of such data has also been applied in a training environment, and according to Reilly (1997), the design of training protocols and standards should always replicate a match and must therefore incoorporate rest periods.

Literature indicates that during match-play, general fatigue usually occurs towards the end of games when players are performing movements of high intensities (Akenhead *et al.*, 2016; Doğramacı and Watsford, 2006). Although it has been found that during games frequent short breaks help assist players recover aerobically, the recovery time is not enough to realise full recovery (Zurutuza *et al.*, 2017). Doğramacı and Watford (2006) illustrated that allowing more frequent substitutions in soccer could help the maintenance of a higher workload during the entire period of high-intensity exercise and ultimately help achieve more significant involvement in their games. Beato *et al.* (2016; 2018a), discussed that recovery periods, as well as activities, are essential in enabling athletes to reduce the accumulation of muscle and blood lactate and facilitate muscle substrate repletion.

Di Salvo *et al*. (2006) validating the use of Prozone ® Sports Ltd., video-motion analysis tool, reported that the use Prozone provided an accurate estimation of different movement velocities performed by athletes on the pitch. A high correlation coefficient as well as reliability coefficients were noted when the researchers compared the mean velocities determined using Prozone and the timing gates. Results showed that when using the Prozone video analysis tool, there was a limited human error when the motions of players were tracked as compared to using multiple cameras. Further, using a Bland-Altman analysis, the authors report that the discrepancy between the two methods was 0.127. Such observation helps to explain the differences in accuracy and reliability when using the video-motion analysis compared to camera motion analysis, allowing the system to track all players simultaneously in real time on the pitch as opposed to only one individual. The advantage of using video motion analysis tools such as Prozone was further documented (Di Salvo *et al*., 2006). When comparing this to previous camera-based systems, it was found that the cameras only provided the analysis of a single payer on the pitch and that an operator was required to handle them during the entire course of activities. In addition, the cameras required lengthy analysis whenever a player was being tracked, unlike Prozone, which is simpler when tracking and analysing players. However, using systems such as Prozone does come with high costs and requires multiple cameras to be installed. In addition, a computerised network with a dedicated operator is required to run the data collection and subsequent analysis and unless carefully designed and validated, data collected might be inaccurate (Di Salvo *et al*., 2006). However, with recent developments, further objective information and analysis of performance variables is continuously progressing.

The literature offers many studies on VMA, but the main advantage these systems confers related to the possibility of automatically evaluating performance not only through determiantion of match-play activity through attainment of speed thresholds ('traditional VMA', as shown in Table 2.1, Di Salvo *et al*., 2007), but also by attributing a specific metabolic cost related to acceleration and deceleration actions, thus expanding on the description of game play with an energetic approach (Table 2.2, Osgnach *et al*., 2010).

Table 2.1. Differences between the first and the second half according to positional roles [reproduced from Di Salvo *et al*., 2007].

Roles	*0-11 km/h*	*11.1-14 km/h*	*14.1-19 km/h*	*19.1-23 km/h*	*>23 km/h*
CD	n.s.	1st half > 2nd half $p<0.05$	n.s.	n.s.	n.s.
ED	n.s.	n.s.	n.s.	n.s.	n.s.
CM	2nd half > 1st half $p<0.001$	1st half > 2nd half $p<0.001$	1st half > 2nd half $p<0.01$	n.s.	n.s.
EM	2nd half > 1st half $p<0.05$	1st half > 2nd half $p<0.05$	n.s.	n.s.	n.s.
F	n.s.	1st half > 2nd half $p<0.05$	n.s.	n.s.	n.s.

n.s. = nonsignificant differences

Table 2.2. The mean ± SD of values of T (s), D (m), EC ($J \cdot kg^{-1} \cdot m^{-1}$) and corresponding EEE ($kJ \cdot kg^{-1}$ or $kcal \cdot kg^{-1}$) during the entire match in each of the acceleration and power categories [reproduced from Osgnach *et al*., 2010].

Acceleration Category	*T (s)*	*D (m)*	*EC ($J \cdot kg^{-1} \cdot m^{-1}$)*
MD (<-3 $m \cdot s^{-2}$)	50 ± 16	188 ± 65	>3.41
HD (from -3 to -2 $m \cdot s^{-2}$)	128 ± 29	411 ± 98	From 2.38 to 3.41
ID (from -2 to -1 $m \cdot s^{-2}$)	448 ± 68	1176 ± 206	From 2.38 to 2.77
LD (from -1 to 0 $m \cdot s^{-2}$)	2282 ± 120	3821 ± 335	From 2.77 to 4.64
LA (from 0 to 1 $m \cdot s^{-2}$)	2152 ± 102	3587 ± 328	From 4.64 to 7.81
IA (from 1 to 2 $m \cdot s^{-2}$)	461 ± 59	1176 ± 184	From 7.81 to 12.03
HA (from 2 to 3 $m \cdot s^{-2}$)	133 ± 29	411 ± 95	From 12.03 to 17.28
MA (>3 $m \cdot s^{-2}$)	51 ± 18	180 ± 67	>17.28

As detailed in the Theoretical Model section, the EC of accelerated and decelerated running was obtained from the individual acceleration values, and the corrisponding ES and EM was obtained with equation 4; the so-obtained results were then multiplied by the grassy terrain constant (KT = 1.29).

Power Category	*T (s)*	*D (m)*	*EEE*
LP (from 0 to 10 $W \cdot kg^{-1}$)	3818 ± 299	4647 ± 230	19.01 ± 1.21 $kJ \cdot kg^{-1}$ 4.54 ± 0.29 $kcal \cdot kg^{-1}$
IP (from 10 to 20 $W \cdot kg^{-1}$)	1173 ± 161	3435 ± 572	16.41 ± 2.34 $kJ \cdot kg^{-1}$ 3.92 ± 0.56 $kcal \cdot kg^{-1}$
HP (from 20 to 35 $W \cdot kg^{-1}$)	461 ± 91	1718 ± 380	11.89 ± 2.39 $kJ \cdot kg^{-1}$ 2.84 ± 0.57 $kcal \cdot kg^{-1}$
EP (from 35 to 55 $W \cdot kg^{-1}$)	163 ± 38	670 ± 173	6.99 ± 1.63 $kJ \cdot kg^{-1}$ 1.67 ± 0.39 $kcal \cdot kg^{-1}$
MP (>55 $W \cdot kg^{-1}$)	91 ± 28	451 ± 144	6.82 ± 2.22 $kJ \cdot kg^{-1}$ 1.63 ± 0.53 $kcal \cdot kg^{-1}$

Both approaches can be applied to track performance through technological tracking. A recent study conducted by Polglaze *et al*. (2018a) noted that traditional approaches related to running speed are not appropriate parameters for the classification of team-sport activities which are comprised of continual changes in speed and direction. However, it has been established that 'critical metabolic power' derived from variable-speed activity appears to be a useful threshold for team-sport activities (Hoppe *et al.*, 2018). Large associations of physiological load have been established between differing team-sport specific exercises, and critical metabolic power classifying team-sports (through a 3-min test; Polglaze *et al*., 2018a). In addition, critical metabolic power also found strong relationships with equivalent heartrate thresholds for stochastic activities during competitive match-play, further supporting the use of critical metabolic power as an appropriate parameter for the classification of intensity for team sport activity.

In recent years, the continuous technological progress of electronic performance and tracking systems (EPTS) has pushed research to compare VMA systems useful for competitions with GPS devices used during training sessions in order to provide techological overlap to monitor and regulate training. In temporal order these multiple comparisons have allowed us to understand more concepts: Randers *et al*. (2010) studied four different systems and they were able to detect performance decrements during a soccer game with large between-system differences in the determination of the absolute distances covered; Buchheit *et al*. (2014b) demonstrate that interchangeability of the different tracking systems (semi-automatic multiple-camera [Prozone], local position measurement [LPM] and GPS) is possible with accurate equations, but care is required given their moderate typical error of the estimate. Linke *et al*. (2018) outlined similar findings between-system differences in the validity of tracking data, implying that any comparison of results using different tracking technologies (Figure 2.1) should be done with caution. Taberner *et al*. (2019) also demonstrated that data obtained through GPS tracking and an optical tracking system (TRACAB), can be interchanged and further emphasise the importance of systems evaluation, to identify where errors exist.

Figure 2.1. (Top) VICON test location on the pitch; (bottom right) scaled 3D model of the Rosenaustadion Augsburg. VICON area (blue), VID camera position (orange) at 21.6 m height and 82.0 m distance from the center spot. Pitch size: 105.0 x 67.0 m; (bottom left) additional camera platform (Linke *et al*., 2018).

2.5: The application of global positioning system (GPS) in field sports

The current GPS technology that is being applied in support of player analysis in sport can be attributed to the initial works and inventions of the 1944 Nobel Laureate winner Isidor Rabi who invented the magnetic resonance method. After the development of the nuclear magnetic resonance method, a series of designs followed with the creation of atomic clocks used to precisely measure timepieces. This formed the basis of the satellite navigation systems. The ability to accurately measure action time, taken from the nuclear clock, is enough to calculate the time it takes for a signal to travel from the satellite to the GPS receiver based on earth, which then expedites the measurement of the distances to the receiver (Steede-Terry, 2000). The availability of four satellites in constant communication with the receiver is enough to determine the exact coordinates and establish the position of an object. Once the position of an object is recognised, the dislodgment over a given period can then be used to find the pace of movement, a factor that has been of interest to scientists for several decades. The ability to measure the speed of changes has also been of great significance not only to coaches but also to athletes engaged in team sports. Earlier research and works performed on GPS have developed rapidly from authentication of GPS accuracy to the measurement of steady-state movements at a steady range of velocities, which has formed the concept of measuring locomotion in human beings and other animals (Terrier *et al*., 2005). It must be noted that GPS signals can be affected by multiple issues; with issues related to (1) synchronicity, (2) the receiver unit, (3) signalling errors, (4) atmospheric conditions, (5) mask angle, (6) ephemeris error, (7) horizontal dilution of precision and (8) satellite lock number issues (Maddison & Ni Mhurchu, 2009).

2.6: The application of GPS in measuring human locomotion

2.6.1. History and development

In 1997, the first attempt was made to validate the use of commercially available GPS devices to measure human movement. The initial participant in this study undertook several trials at different walking and running velocities, after which the data collected from the GPS was compared to a Swiss timepiece. The association between the GPS display and chronometer was found to be n = .99 and 5% constant of disparity for the slope line. The initial investigation was highly promising but failed to provide a gold line standard where scientists could validate and confirm GPS as a valid instrument for measuring velocity. The study was further hampered when the accuracy of the satellite transmission was degraded by the Department of Defense of the United States (Schutz & Chambaz, 1997). However, in 2000, this degradation was ended and subsequently provided ways to examine how GPS could be used to measure velocities of objects. Later tests revealed that it was possible to correct the scrambled signals from the GPS by computing second difference phases through the application of two receivers positioned adjacent to each other and thereby reducing the three-dimensional error which was found during the first experiments (Witte *et al.*, 2005). The method was then used to measure the positional information and accelerometer data. The application of a high precision GPS produced high intra-individual variability throughout. The introduction of the European Geostationary Navigation Overlay Service (EGNOS) and the Wide Area Augmentation System (WAAS) further reduced the GPS inaccuracies and achieved significant improvements in the measurement of velocities and accurate positions in straight line tasking. After this, GPS systems looked at gaining a greater understanding of the effectiveness when changes of direction and changes in velocities are taken (Aughey, 2011).

2.6.2. Reliability and validity of GPS systems in sport

Initially, significant improvements surrounding the validation in the use of GPS to measure velocities and positions of individuals in a straight line were made but, significant challenges remained (Aughey, 2011). Establishing the movement and speed of athletes involved in multiple directional changes seemed difficult. Additionally, there was a need for the GPS to withstand different conditions including different moisture, heat, and other potential impacts before they could be successfully applied in a team-sports environment. In 2003, the first commercially available GPS dedicated for sports was introduced and authenticated and compared to data collected through a computer-based following CBT system. Further comparison with a calibrated trundle wheel helped to approve the application of GPS in measuring distance objects. Nevertheless, despite high correlations of over r = .998, an overestimation of 5%, and a CBT of approximately 6% was established (Aughey & Falloon, 2010). In 2009-2010 further validation of GPS to be used in sports was made when different studies employing slightly different GPS technologies and methodologies were published. Table 2.3 below illustrates some of the studies which have examined and validated the application of GPS in several sports.

Table 2.3. Several validity studies undertaken on global positioning systems specific to field sports.

Author	GPS device	Sampling rate	Parameter	Task	Sport
Akenhead *et al.*, 2014	MinimaxX S4	10-Hz	Instantaneous velocity	10 metre sprint	Soccer
Barbero-Alvarez *et al.*, 2010	SPI elite	1-Hz	Speed	30 metre sprint	n/a
Beato *et al.*, 2018	STATSports Viper	10-Hz	Peak speed	400 metre run, 128.5 metre sports-specific circuit, and 20 metre run	Sport
Castellano *et al.*, 2011	MinimaxX v4.0	10-Hz	Total distance	15 metre and 30 metre sprint	n/a
Coutts & Duffield, 2010	SPI 10, SPI elite and WiSPI	1-Hz	Total distance	Running circuit (128.5 metres)	Team-sport
Duffield *et al.*, 2010	SPI elite and MinimaxX v2.0	1-Hz and 5-Hz	Total distance, peak velocity and mean velocity	Simulated court run	Tennis
Edgecomb & Norton, 2006	SPI 10	1-Hz	Total distance	Marked circuit running; (138 to 1386 metres)	Australian Football
Gray *et al.*, 2010	WiSPI Elite	1-Hz	Total distance	Linear and nonlinear running (200 metres)	Field-based sports
Hoppe *et al.*, 2018	MinimaxX S4 and GPEXE PRO	10-Hz and 18-Hz	Instantaneous velocity	Team-sport circuit run	Team-sport
Jennings *et al.*, 2010	MinimaxX team 2.5	1-Hz and 5-Hz	Total distance	Sprint trials, tight CoD, gradual CoD and team sport circuit (140 metres)	Australian Football
Johnston *et al.*, 2012	MinimaxX team 2.5	5-Hz	Total distance and peak speed	Team sport simulated circuit; (130.5 metres)	Team-sport
Johnston *et al.*, 2014	MinimaxX S4 and SPI-Pro X	10-Hz and 15-Hz	Total distance and peak speed	Team sport simulated circuit; (165 metres)	Team-sport
MacLeod *et al.*, 2009	SPI elite	1-Hz	Total distance	Hockey simulated circuit	Field Hockey
Nikolaidis *et al.*, 2018	Johan GPS	10-Hz	Total distance and speed	200 metre run and 20-m shuttle run endurance test	Soccer
Padulo *et al.*, 2019	Spin_GNSS_50Hz	50-Hz	Total distance and average speed	Soccer-specific runs	Soccer
Petersen *et al.*, 2009	SPI 10, SPI-pro and MinimaxX	1-Hz, 5-Hz and 10-Hz	Total distance	Cricket-specific run; (600 to 8800 metres)	Cricket
Portas *et al.*, 2010	MinimaxX v2.5	1-Hz and 5-Hz	Total distance	Linear run, multidirectional run and soccer-specific run	Soccer
Rampinini *et al.*, 2015	SPI Pro and MinimaxX v4.0	5-Hz and 10-Hz	Total distance, HSR, and VHSR distance	70 metre straight-line shuttle runs	Team-sport
Randers *et al.*, 2010	SPI elite and MinimaxX v2.0	1-Hz and 5-Hz	Total distance	Match running	Soccer
Reinhardt *et al.*, 2019	Polar Team Pro System (PTPS)	10-Hz with 200-Hz IMU	Sprint time and average acceleration	20 metre linear sprint	Soccer
Roe *et al.*, 2016	Catapult Optimeye S5	10-Hz	Maximum sprint velocity	3 maximal 40 metre sprints	Rugby Union
Varley *et al.*, 2012	MinimaxX v2.0 and MinimaxX v4.0	5-Hz and 10-Hz	Instantaneous velocity	Straight-line running	Team-sport
Vickery *et al.*, 2014	MinimaxX v2.0, MinimaxX v4.0 and SPI-Pro X	5-Hz, 10-Hz and 15-Hz	Total distance, mean speed and peak speed	Short high-intensity run and multi-directional CoD run	Cricket, Tennis and Team-sport
Waldron *et al.*, 2011	SPI Pro	5-Hz	Total distance	Sprint (10 to 30 metres and 10 metre moving)	Rugby League
Yanci *et al.*, 2016	MinimaxX v4.0	10-Hz	Sprint time	20 metre sprint	Soccer

Note. The manufacturer of SPI elite, SPI Pro, SPI 10 and WiSPI is GPSports, and the manufactorer of MinimaxX v2.0, 4.0 is Catapult Innovations.

Rampinini *et al*. (2015) compared two high-frequency GPS (5 and 10-Hz), with a radar system (Stalker ATS, Radar Sales, Minneapolis, MN, US) considered together with the laser systems the gold standard for the measurement of instantaneous speed. Only 10-Hz GPS demonstrated a sufficient level of accuracy for quantifying distance covered at higher speeds or time spent at very high power (Figure 2.2).

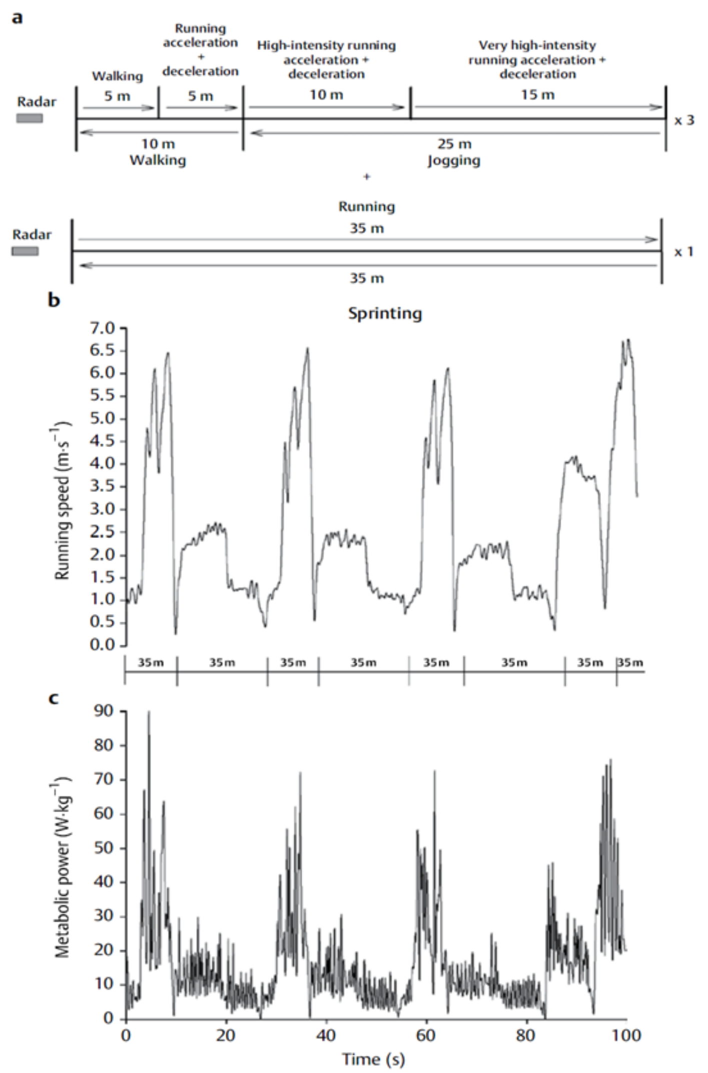


Figure 2.2. Schematic representing the activities performed during each bout of the intermittent shuttle running (panel **a**) and an example of running speed measurement (panel **b**) and metabolic power calculation (panel **c**) using the radar system (reproduced from Rampinini *et al*., 2015).

After several studies attempted to validate the application of GPS in sports the validity and reliability needed futher consideration and to review its usefulness. As a result, several researchers embarked on experiments to test how GPS could effectively be applied in soccer games (Akenhead *et al.,* 2014; Hoppe *et al.,* 2018; Rampinini *et al.,* 2015). The physiological demand imposed on soccer players has been of great importance and subject of extensive research for several decades.

The following section considers previous research regarding the metabolic power needed by soccer players. Earlier assessments of the metabolic demands assessed through body temperature revealed that the average metabolic load of soccer players is almost 70% of the $\dot{V}O_{2max}$ (Mohr *et al.,* 2005), and direct measurement of the latter is not appropriate to provide data on high-intensity exercise.

Soccer is a sport that involves both the aerobic and anaerobic processes (Di Salvo *et al.,* 2007). Energy expenditure assessments have been done using continuous HR recordings allowing for the analysis of aerobic performance based upon the linear relationship between cardiovascular responses and oxygen uptake (Manzi *et al.*, 2014). This study proposed a new approach that could be used to analyse the performances of soccer players by considering patterns of accelerated and decelerated running. Although this approach does enable quantification of the energetic demands of a soccer player during actual match- play it does not express the nature of the involved metabolic pathway in relation to exercise undertaken during the match. Further, using different movement conditions and considering the opposing interplay of speed and acceleration to obtain a given metabolic power results ina method limitation when considering this for training prescription. Nevertheless, observations have also suggested that higher levels of metabolic power are required when playing teams of a higher opposition, with altering patterns of accelerated and decelerated running (Folgado *et al.*, 2014). The level of opposition dictates the amount of energy a professional soccer players needs to sustain the higher demand of metabolic power. In addition, playing against teams which have a numerical superiority (11 *vs.* 10), has shown that the disadvantaged teams tend to have an increased demand for team synchronization which ultimately result higher levels of metabolic power. Gaining a better understanding about the difference in required energy levels of players when facing different types of opponents and how different formations affect metabolic power will provide more information related to soccer performance.

Folgado *et al*. (2014). It was established that while some of the distances that players cover at different movement speeds vary highly between soccer games as a result of the opposition faced. The timing of the player's movement is highly sensitive to the level opposition and differences in movement types are present, with higher demands of high intensity movements required when facing higher level opposition. The outcomes of this study emphasise the need to further assess the relation between time motion variables and movement synchronisation tendencies to help gain new insights when further analysing the performances of soccer players. However, despite these considerable efforts at analysing soccer player's performance and the need for movement synchronisation, the authors did not conclude how the synchronisation levels affected the metabolic demands of players. Therefore, there is a need for a new study to ascertain how high levels of synchronisation can reduce the energy costs during high-intensity match play.

Through the use of a multiple camera semi-automatic system information regarding running speed and distances covered by athletes have been collected. In a study that compared three methods of tracking technologies, which included the GPSports technology, the LPM technology, and the semi-automatic multiple-camera technique, it was discovered that using the three systems provide different data and metrics but that the magnitude between the differences were based on the size of the pitch (Buchheit *et al*., 2014b). The differences established between the three systems are an issue of concern for the sports scientists and coaches and each has advantages and disadvantages. It is important coaches and practitioners understand the implications of each system when comparing/interpreting training/match activities measured by different systems. Observations made between GPS unit variability, within-unit chipset changes and software updates can have a substantial impact on the different metrics and must be considered when monitoring players (Buchheit *et al*., 2014a). Thus far, only a few studies have been conducted to examine the differences between semi-automatic multiple-camera analysis and the GPS analysis (Buchheit *et al*., 2014b; Randers *et al.,* 2010). Findings have shown that the distances recorded form the GPS differ moderately to greatly when through comparing with the reference measures, the typical error of the estimate (both in % and in standardised units) and the magnitude of the correlations between the systems when compared to the data collected from semi-automatic multiple camera analysis. Sonderegger *et al*. (2016) showed that in addition to the system used, the size of the pitch was an essential determinant of the accuracy of these methods. Delaney *et al*. (2016), also notes the size of the pitch was positively related to the overall distances that athletes ran at high speeds. Therefore, when calculating the energy requirements of athletes, it is essential to consider the size of the pitch where the athletes will be assessed, with observations establishing differences according to pitch size and system utilised. The observation is particularly significant to the coaches and sports doctors who must prepare their players for the different pitch sizes and playing styles.

2.7: High-intensity activities in soccer

Match analysis reveals football players at the elite level typically cover 9–14 km during a game with movements of high intensity accounting for 5–15% of match-play (Faude *et al.* 2012). Bradley *et al*. (2009) examined the effects of high intensity running on soccer players in the English Premier League. It was determined that the use of time-motion could be helpful in quantifying the physiological needs of soccer players and thereby providing a conceptual framework that could be used to measure the performances of specific training. Bradley *et al*. (2009) noted that high intensity running in elite leagues such as the English premier league imposes significant physiological demands on the modern elite players especially central midfielders and central defenders. The fact that the study was compatible with the results found when players from other leagues were examined (Chmura *et al.*, 2018; Hoppe *et al.*, 2015) is a testament that high-intensity running is one of the main determinants of the physiological and physical needs among soccer players around the world. It is essential to examine how increased physical demands correlate with metabolic power and how players from different soccer leagues require different metabolic strengths. High-intensity games and time spent performing in games are especially important as they determine the amount and the extent to which elite players need energy. Despite the differences observed in high-intensity running between players of different positions, players must be able to maintain the ability to perform actions of high intensity towards the end of the game. Therefore, it can be concluded that elite players taking part in high-intensity running leagues such as the English Premier League still require the ability to work at maximum metabolic power as they near the end of their matches. The research by Bradley *et al*. (2009) also reported that the average recovery time during high-intensity running bouts in the English Premier League increased significantly over the duration of the entire game. The outcome being a distance deficit of about 30% for high intensity running regardless of whether the team/player was in possession of a ball or not. During an average game, the high-intensity activity tend to reduce by about 50% after the first five minutes. The significance of this observation is that during a soccer match, the instances where players could show high power running keep on interchanging at periodic intervals of 5 minutes (Osgnach *et al*., 2010). With fatigue being one of the factors that determines the level of high intensity running in soccer games, unless a player has a high metabolic replenishment, it could result in the player being unable to continue playing at a high level and thus impair contributions to on pitch activity.

2.8: Future developments in the application of GPS to field sports

It has been suggested that the future demands of GPS technologies in sports will primarily focus on several primary areas (Aughey, 2011; Buchheit *et al.*, 2014b). Firstly, the GPS will be applied to examine the greater integration of movement data especially those associated with fitness, tactical, physiological, and strategic data. The second area will involve the application of GPS in how the GPS can be integrated with the inertial sensor data. Thirdly, the future of GPS will involve further miniaturisation with a possible increase in sample rates to help accuracy and reliability of data. Further, considering the many advantages and disadvantages each GPS unit has, the magnitude of the between-system differences will be assessed looking at the effect of both pitch size and the variable of interest.

2.9: Technology around the concept of metabolic power (MP) and energy cost (C) in soccer

GPS are devices which enable the collection and analysis of movement data and thereby allow the evaluation of the most critical physical actions performed by players such as the distances they cover, the amount of time they spend while running at high speeds, and the number of changes in direction they make during a match (Akenhead *et al.,* 2014).

The concept of metabolic power (MP) applied to soccer has revolutionised the player specific demand of high-intensity activity. To broaden the vision of performance with an energetic approach that takes into account all the kinematic aspects (speed and accelerations), it must start with the concept of energy cost (C). Osgnach *et al*. (2010) calculated the metabolic power indirectly using a biomechanical stratagem (Figure 2.3) to use energy equivalence starting from the energy cost equation of Minetti *et al*. (2002) as shown in Figure 2.4.

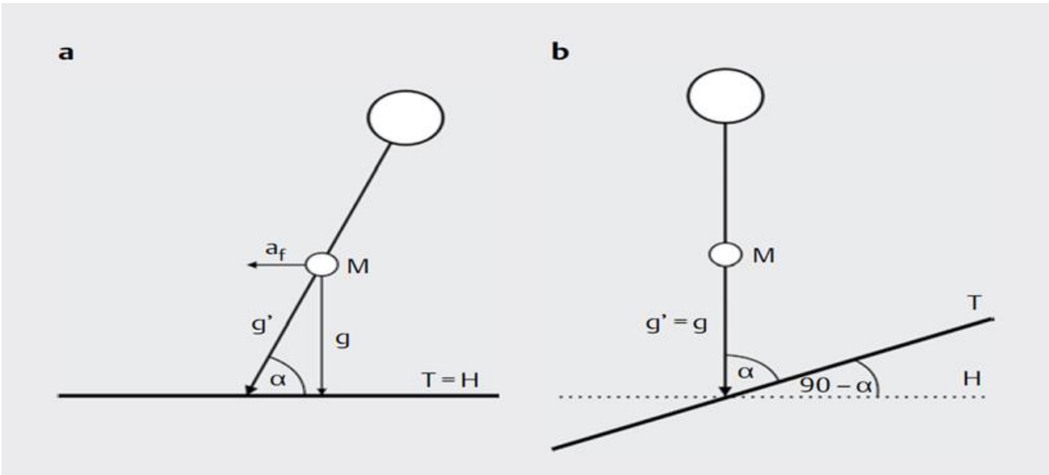


Figure 2.3. a accelerated running on flat terrain; **b** uphill running at constant speed. M, body mass; a_f, forward acceleration; g, acceleration of gravity; $g' = (a_f^2 + g^2)^{0.5}$, vectorial sum of a_f and g; T, terrain; H, horizontal; α, angle between runner's body axis and T; 90 - α, angle between T and H (reproduced from di Prampero *et al*. 2005).

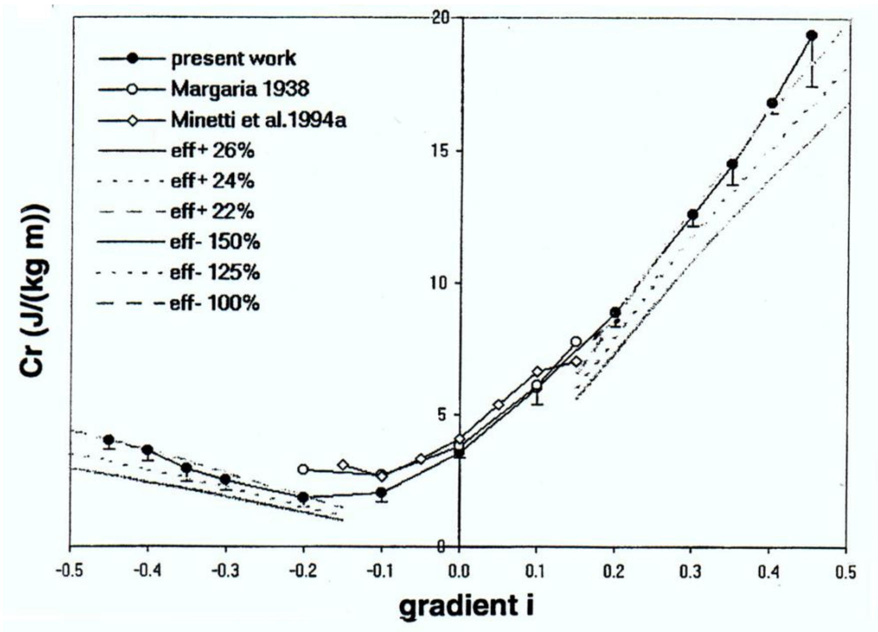


Figure 2.4. Metabolic energy cost of running (C_r) as a function of the gradient from the work by Margaria (1938; 1963) and Minetti *et al*. (1994). Average energy cost of running for each gradient have been reported. To accurately describe the relationship between C_r and the gradient *i* within the investigated range, 5th-order polynomial regressions were performed, that yielded: $Cr_i = 155.4i^5 - 30.4i^4 - 43.3i^3 - 46.3i^2 + 19.5i + 3.6$ ($R^2 = 0.999$) (Minetti *et al*. 2002).

Knowing the energy cost of movement at constant speed(s), accelerations, decelerations and their combinations, it is possible to build a graph able to explain the relationship between movement and metabolic power output. Osgnach *et al*. (2010), using the models of di Prampero *et al*. (2005), illustrated in a simplified way this concept (Figure 2.5).

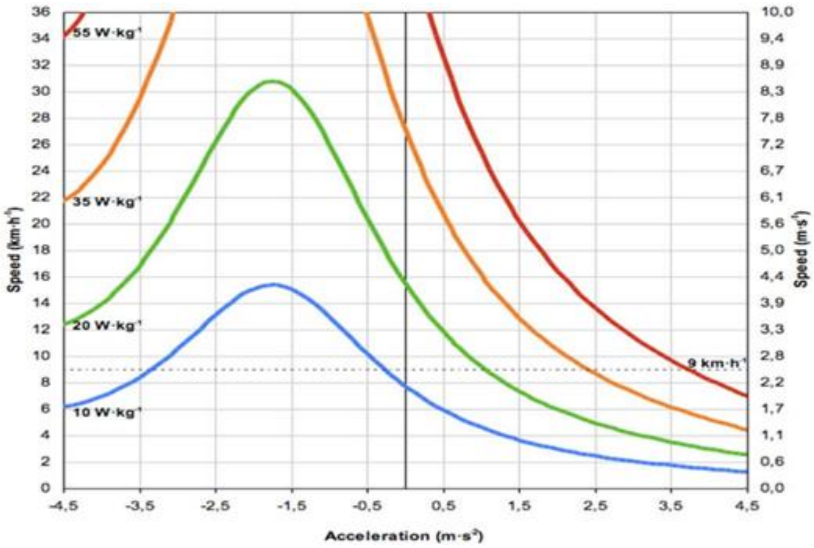


Figure 2.5. Isopower relationships calculated as a function of speed (y-axis) and acceleration (x-axis). A speed of 9 km·h^{-1} (horizontal sketched line) yields different power outputs depending on acceleration.

Following Figure 2.5, if we consider a constant speed of 9 km·h^{-1}, the metabolic power would amount to approximately 13 W·kg^{-1}, whereas at the same speed, but with an acceleration of 1 m·s^{-2} or 2.4 m·s^{-2}, the metabolic power would increase to 20 or to 35 W·kg^{-1}. Conversely, decelerated running would bring about a reduction of metabolic power (Osgnach *et al*. 2010).

Di Prampero and Osgnach (2018), in a recent review of the metabolic power model in soccer, suggested the inclusion of walking phases [which are typically present in large proportions in match-play; Bradley *et al.*, 2013]. In including this energy cost estimates for walking which is different (C_w) to that of the constant speed race (C_r), a new value for the constant term of the enrgy cost equation i.e. 2.5 J·kg^{-1}·m^{-1} has been proposed. Figure 2.6 explains how this in-depth analysis is able to represent the different energetic amounts according to the activities carried out.

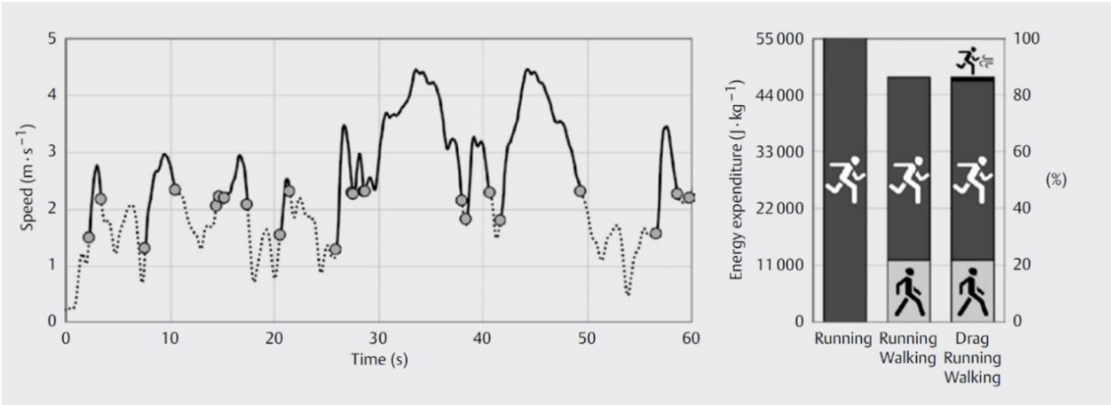


Figure 2.6. Left: the time course of the speed during 60 seconds of an actual match: broken line = walking; continuous lines = running. Open circles denote the transitions between the two gaits. Right: the left column = overall energy expenditure, as calculated neglecting energy cost differences between walking and running. The middle column = overall energy expenditure due to walking (white) or to running (grey). The right column = the energy spent against the air resistance is indicated by the uppermost black part (reproduced from di Prampero *et al*., 2018).

Given that such a metabolic power model either in its orginal iteration or in its recently modified form (Osgnach *et al.*, 2010; di Prampero *et al*., 2018) takes estimates the energy cost of the activity, it is possible to express the total energy expenditure can be expressed as equivalent distance (ED) instead of TDC because it depends on both TDC and on "how[intense]" the TDC was performed. Although different players could have covered the same TD, the use of ED allows the identification of different metabolic energy expenditures, thus allowing an estimate of the "true" overall energy expenditure regardless of the actual distance covered. As shown in Figure 2.7, on average, ED is linearly related to TD, being approximately 20% higher (Osgnach *et al*., 2010).

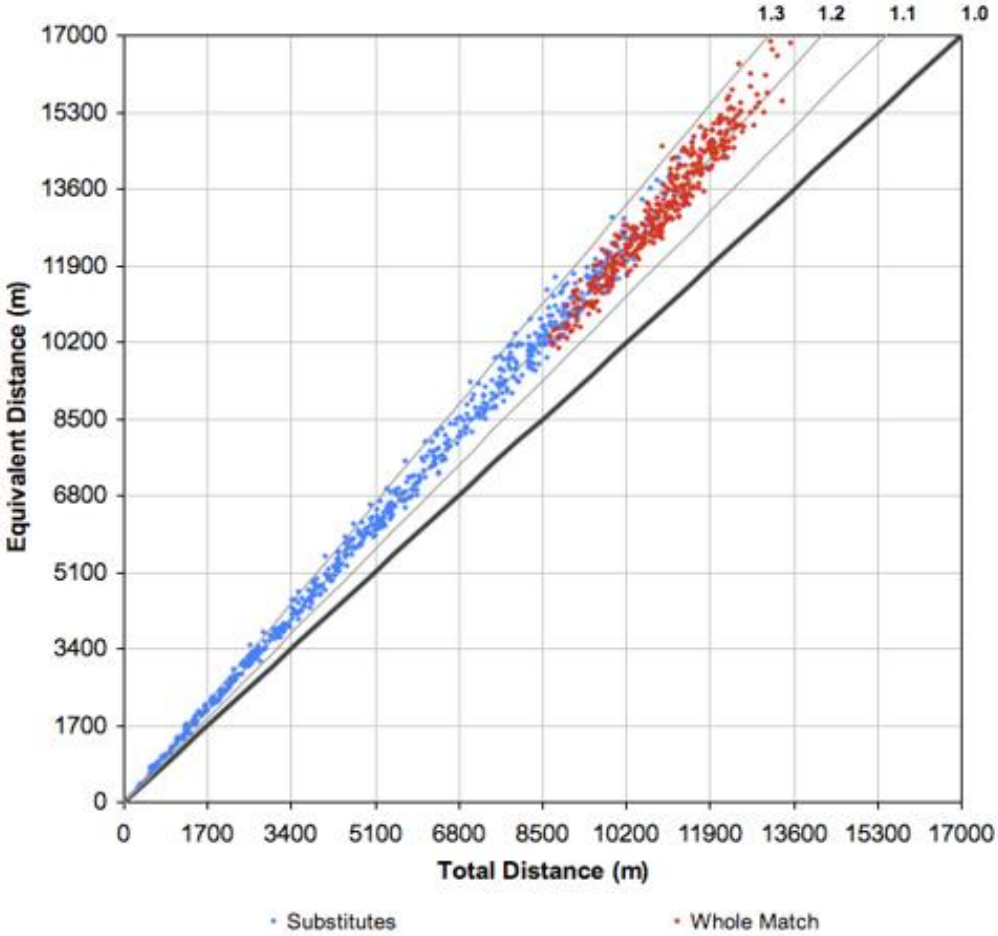


Figure 2.7. ED is plotted as a function of TDC. Players who complete the whole match are symbolized in red circles, whereas substitutes are symbolized in blue circles. Every straight line represents a constant ratio between ED and TDC defined as equivalent distance index (EDI) (reproduced from Osgnach *et al*., 2010).

Recently , Minetti *et al*. (2018) have updated the concept of equivalent slope, upon which the models of Osgnach *et al.* (2010) have been based by extending his previous model (Minetti *et al*., 2002) to include a deceleration component into the model, and revised the predictive equation to be applied to much higher rates of speed change. The extension to a wider range of acceleration benefits from recent metabolic results (Giovanelli *et al*., 2015) of uphill, constant speed running up to I = +0.84 (where i is the gradient in terms of the tangent of slope angle) which corresponds to level accelerations up to 8.24 $m \cdot s^{-2}$, according to the Equivalent Slope (ES) equation.

Buchheit *et al*. (2015a), indicates that in applying systems such as ‘energetic approach’, model it is easy for individuals to implement the use of GPS to estimate the amount of energy expenditure as well as establishing metabolic power derived from the acceleration and deceleration movement data. Sports scientists and coaches alike have found the importance of GPS invaluable due to its increased reliability and validity in recording the actions of athletes. Previous researchers such as Varley *et al*. (2012; 2017) and Stevens *et al*. (2014) have demonstrated that GPS at a range of sample frequencies is a highly reliable instrument which coaches and other fitness personnel can use to evaluate the external training loads. However, important caveats are applicable in that Buchheit *et al*. (2014a), noted that during small distance tracks (40-m) as well as quick movements (19.8 $km \cdot h^{-1}$), the reliability of GPS tended to decrease. However, importantly, Dwyer and Gabbett (2012) found that the use of higher frequency GPS instruments were more valid than the use of low-frequency GPS instruments. Johnston *et al*. (2013) noted that GPS with frequencies between 10 and 15-Hz were classified as high frequencies while GPS using rates in the range of 1 and 5-Hz were deemed low-frequency GPS. The classification of GPS into different frequencies is necessary as it helps to determine the validity and reliability and, therefore, provides information as to which is the most appropriate GPS to apply under different sport data acquisition conditions. Waldron *et al*. (2011) showed that different proprietary GPS brands express considerable variability both between and within the same brand of GPS units. Domene (2013) indicated that for coaches and sports scientists obtaining the accurate acceleration and deceleration metrics is as important as the validity of the distance covered and velocity data; in the context of in soccer application both elements are essential factors in estimating and determining the training intensity and volume where metabolic power data are acquired. The need to validate any GPS before use when determining training load particulary with metabolic power is essential as it ensures calibration to the most frequently areans of application. Beato *et al*. (2016) supporting this notion that each systems validty and relaibility in the context in which it will be used should be assessed noted that when video analysis and GPS systems were compared whilst measuring player velocity and other movement data, the most accurate and valid/reliable instrument was the video analysis. Such reports are not uncommon in the literature.

Witte and Wilson (2004), showed that GPS tends to underestimate shuttle speeds, and this leads to the decreased accuracy of GPS instruments when used in high-speed movements and small distance tracks, altough this was performed with lower sample frequency system. Similarly, Aughey (2011) reported that the accuracy of GPS is significantly degraded when athletes make rapid changes in direction. This finding also has been increasingly reported. Therefore, it can be concluded that the inaccuracies recorded when using GPS instruments can be attributed to the errors involved in determining shuttle speeds and distances (Aughey, 2011; Buchheit *et al.,* 2014a; Hoppe *et al.*, 2018). Buchheit *et al*. (2014a) also reported this notion and claimed that inter-unit reliability and accuracy of GPS are negatively affected by multi-directional movements of athletes, a critical movement characteristic typical of all team sports. In addition, it has been established that football stadiums and other specific surroundings afect the strength of the signals the GPS unit receives. Using GPS potentially reduces the amount of available sattelites and ultimately the transfer of data, thus resulting in lost data. Ultimately, this reduces the reliability of the data, therefore suggesting significant caution when applying this data collected (Maddison *et al.*, 2009). Other considerations that need to be taken into account are that accuracy of data is dependant on the location and the receiver density (Kao *et al.*, 2013). Lastly, although sampling rates above 10 Hz have further improved the reliability and validity of GPS data, other more technical aspects such as the antenna, the microprocessor and its data processing algorithms, positioning of the devices on the body, and environmental conditions have shown to affect validity and reliability (Hoppe *et al.*, 2017; Malone *et al.*, 2017).

Osgnach *et al*. (2010) examined the metabolic power and energy cost imposed on elite players, during typical soccer match lasting 90-minutes, and noted the average expenditure of energy was 61.12 ± 6.57 $kJ \cdot kg^{-1}$ (14.60 ± 1.57 $kcal \cdot kg^{-1}$) per player. The data also indicated the total amount of energy spent on high-intensity activities [high power] was more than 26% during a 90-minute game. Cumulatively the metabolic power consumed by athletes during high-intensity activities was explicitly higher when a video motion analysis technique was applied. When low-intensity running was considered it reported significantly lower metabolic power estimates in athletes. The video analysis method was also found to provide additional parameters related to velocity and distance covered that sports personnel could use to examine the profile of players. Further, Brown *et al*. (2016) report that when players played at higher altitudes, their work rate was significantly reduced due an increased recovery time period between high intensity running and other effort activities. Further, Buchheit *et al*. (2015a) discovered that the time of the day also played an essential role in determining the metabolic power and energy of athletes. During morning hours, energy demands tended to be lower than when players played at other times of the day when temperatures were at their circadian peak value. Further investigations looking at the influence of diurnal variations on metabolic power needs of athletes, discovered that the metabolic needs among elite players were higher during the afternoons than during the morning.

Varley *et al*. (2017) set out to analyse the match performances of high-standard players with reference to fatigue development during competitive soccer matches using a computerised time-motion analysis where every player was video-filmed at close range. Data indicate that elite players perform at high intensity (speeds of 14.3 $km \cdot h^{-1}$ or higher) for long periods of time when compared to non-elite players. Furthermore, the elite players express improved intermittent recovery when compared to the professional players from sub elite standards. The observations were made independent of the playing positions of the players. The results also further support the idea that the work load demands of the players were dependent on the playing positions where it was affirmed that the defenders covered the least distances and made the least high intensity running during games (Bradley *et al*., 2013; Varley *et al*., 2017). Vigne *et al*. (2010) claimed that when training elite players, it is necessary to focus the attention on improving their ability to perform intense exercises and to recover from periods of high-intensity workouts rapidly. The differences noted on the physical performance of the elite players and those from the lower level leagues is an indication of the different physical activity and effort requirements needed for varying intensities of the game. High-intensity level games, require the players more energy to meet the increased physical demands. According to Vescovi and Favero (2014), players at all levels showed a general decline in running intensity towards the end of the game, and this is important as it helps explain that soccer players tend to tax their physical capacities as the game goes on. However, this physical demand should not be taken as a represenative model of all players as different positions will require different levels of energy expenditure.

High-intensity indicators should be interpreted cautiously and repeated match observations are recommended to establish meaningful high-intensity profiles of the players both collectively and as a function of different positions. Differences among playing positions and relationships with explosive physical abilities indicate that metabolic power analyses can provide new insights into the mechanics and energetics of soccer (Hoppe *et al*., 2017).

Table 2.4 summarizes most of the concepts expressed in this paragraph by comparing the energetic approach based solely on speed, and pointing out how the cost of accelerations and decelerations, is able to broaden the study of human locomotion towards specific movements of some team sports by inserting in the total energy calculation: changes of direction (CoD), backward runs, lateral runs (Osgnach *et al*., 2018).

Table 2.4. Summary of the main characteristics of the speed- and energy-based approaches with comments highlighting the principal differences between the two (Osgnach *et al.*, 2018, modified after Polglaze *et al.*, 2017).

PARAMETER	SPEED-BASED APPROACH	ENERGY-BASED APPROACH	COMMENTS
Volume	**YES** Total distance (m)	**YES** Total energy ($J \cdot kg^{-1}$) Equivalent distance (m)	The total distance is a correct estimate of the "volume" only if the speed is constant. In the energy-based approach this is expressed by the equivalent distance, thus also taking into account the acceleration/deceleration phases.
Intensity	**YES** Average speed ($m \cdot s^{-1}$)	**YES** Average metabolic power ($W \cdot kg^{-1}$)	The average speed is a correct estimate of the intensity only if the speed is constant. In the energy-based approach, the average metabolic power also takes into account the acceleration/deceleration phases.
Intensity distribution	**YES** Speed bands: - Total time (s) - Total distance (m)	**YES** Metabolic power categories: - Total time (s) - Total distance (m) - Total energy ($J \cdot kg^{-1}$)	In the energy-based approach, the metabolic power categories also take into consideration the acceleration/deceleration phases, which is not the case for the speed bands.
Peak activities	**YES** Peak speed ($m \cdot s^{-1}$) Peak acceleration ($m \cdot s^{-2}$) [1] Peak deceleration ($m \cdot s^{-2}$) [1]	**YES** Peak metabolic power ($W \cdot kg^{-1}$) Peak eccentric mechanical power ($W \cdot kg^{-1}$)	Peak metabolic power takes into account both acceleration and velocity. Peak eccentric mechanical power, as such, is a good index of the mechanical stress on muscles and joints. This is not discussed in the present review.
High-intensity phases	**YES** High-speed phases based on a fixed/individual speed threshold: - High-speed running time (s) - High-speed running distance (m) - Occurrences at high-speed running (#) High acceleration phases based on a fixed/individual acceleration threshold: - High acceleration time (s) [1] - High acceleration distance (m) [1] - Occurrences at high acceleration (#) [1]	**YES** Anaerobic phases based on the individual VO_2 max: - Total time above VO_2 max (s) - Total distance above VO_2 max (m) - Total energy above VO_2 max ($J \cdot kg^{-1}$) - High metabolic power events (#) - Anaerobic energy ($J \cdot kg^{-1}$) - Anaerobic index (%) - Average event duration (s) - Average event metabolic power ($W \cdot kg^{-1}$) - Average recovery duration (s) - Average recovery metabolic power ($W \cdot kg^{-1}$)	The parameters estimated from the energy-based approach take into account the physiological characteristics of the player in question. A brief discussion and a few examples are reported in the two sections that follow.
Temporal changes (1st half *vs* 2nd, 15 min time periods)	**YES** Trend of volume and intensity parameters	**YES** Trend of volume and intensity parameters	The differences between the two approaches in terms of estimated volume and intensity are discussed above
Cost of acceleration/deceleration	**NO**	**YES**	
Acceleration relative to the initial speed	**NO**	**YES**	
Erraticness	**NO**	**YES** - Equivalent distance index (%)	The quality of being erratic (i.e., the opposite of being constant)
Changing direction	**NO**	**YES** [2]	
Backward/lateral locomotion	**NO**	**YES** [3]	
Vertical actions	**NO**	**NO**	
Static actions	**NO**	**NO**	
Collisions/tackles	**NO**	**NO**	
Sport-specific skills	**NO**	**NO**	

[1] They do not consider the starting speed.
[2] Only the cost of rotation is not considered, whereas deceleration and acceleration are included in the change of direction's overall cost.
[3] The cost of back and lateral locomotion can be corrected for a more accurate estimate of energy expenditure.

2.10: Performance characteristics according to playing position in soccer

Vigne *et al*. (2010), examined the number of activities undertaken in different playing positions in Italian soccer matches. Differences were established between the two halves of a game and revealed that different situations require different efforts and quantification of activities. The study discovered that the average distance athletes cover was 121.0 ± 9.5 meters per minute which equates to approximately 10.94 kilometres in a 90-minute game and metabloic neeeds differed according to player. Similarly Ade *et al*. (2014) who found that on average a player covers 10.80 kilometres in a 90-minute match. However, the re-occurring issue is always to correctly categorise these distances into different segments depending on the intensity of the activity. Ardigò *et al*. (2015) noted that out of the average 10.8 km athletes covered during a 90-minute match, 38% was spent walking, 29.5% spent jogging, 13% spent running at speeds of between 13 and 16 $km \cdot h^{-1}$, 9.8% spent sprinting, while the remaining 8.4% covered running at speeds between 16 and 19 $km \cdot h^{-1}$. The authors concluded that the key to success in soccer was the ability to perform intense and brief bursts of activities and efforts with minimal periods of recovery. Further, it was reported that the work/recovery ratio in a 90-minute game was approximately 1:8. These finding are important in that it can help prepare soccer players for a 90-minute match so that they can optimise movements according to time. Significant differences between the first and second half of soccer games was accounted for by the the amount of time spent on low-intensity activities which was higher in the second half than in the first half, potentially because of fatigue.

Clemente *et al*. (2013) examined the activity profiles of soccer players who took part in the 2010 World Cup with the objective of obtaining velocity and distance variables which were most influenced by playing positions (Figure 2.8). To do so, the distances of every player were examined to discover the characteristics which described the most successful team. The authors found that the distances every player covered varied from game to game and from one position to another. In this study, unlike previous research performed by Ekblom (1986), the midfield players covered the greater distance as opposed to the wingers. The same study also revealed that defenders covered the least distances during a 90-minute match. Davis and Brewer (1993) and Datson *et al*. (2014) also indicated that in a soccer match, regardless of the extra time and over time, the least distances were covered by the central defenders because their sprinting time was limited.

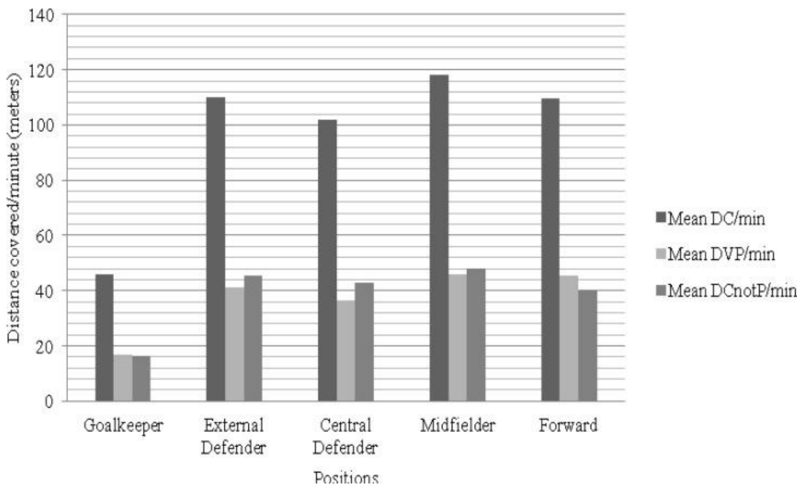


Figure 2.8. The average distances covered by the players during the 2010 World Cup matches (according to Clemente *et al*., 2013).

Osgnach *et al*. (2016) also supported these observations and illustrated that the midfield players covered the most distance closely followed by the forwards. The main reason for this observation was that the midfield players act as the link between the offense and the defence. Castellano *et al*. (2011), reports that midfield players are the most essential members in team sports because statistically, they cover the most distances whenever their team is in possession of the ball. Haugen *et al*. (2014) further suggests that elite defenders and strikers cover almost the same mean distances ($m \cdot min^{-1}$) during a match with central defenders achieving the lowest distance covered of any outfield player.

2.11: The effects of anaerobic and aerobic processes

Stevens *et al*. (2015) provided evidence that professional soccer players engage in intermittent high intensity running and efforts and it has been found that almost 98% of this running is under 10-s in duration. Stevens *et al*. (2014) argued that high intensity runs among elite athletes were between 2.5 and 4 seconds and that midfielders covered the greatest distances during a game. Gaudino *et al*. (2013) also noted that anaerobic sources and processes provide minor energy requirements during soccer competition with high anaerobic contributions apparent in situations where the players made high-intensity bursts. In a study by Clemente *et al*. (2013) found that the majority of high-intensity running and efforts during a game took only 2 seconds and that only 10% of high-intensity running took up to 10 seconds or longer. Bangsbo (1994b), discovered that adenosine triphosphate (ATP) and muscle creatine phosphate (CP) provided the primary substrate for the highest intensity bursts players performed during soccer match-play.

Several researchers have shown that aerobic and glycolytic sources have significant contributions to the energy sources players require during games and exercises. Walker *et al*. (2016), noted that aerobic sources of energy were shown to provide the energy athletes need when performing repeated sprints when using running ergometry. Ward-Smith and Radford (2000) showed that the scaling of the 15 minutes observation to over 90 minutes is an indication that the outfield players can perform 10-s sprints 18 times more than the total energy demand which could be derived from either anaerobic or aerobic process. A range of recovery periods between high-intensity activity bursts was found to exist and that only 57% of all the recoveries took less than 20 seconds while only 3.5% needed more than 90 seconds or more. The importance of this study is that it helped to highlight that the recovery range between bursts could significantly implicate the energy system which players utilise during high-intensity efforts. Waldron *et al*.

(2011) showed that the accumulation of blood lactate and athlete performance is correlated and resulted in a decrease in performance over five 6 seconds maximal sprints efforts taken when the recovery provided was 60 seconds.

Ward-Smith and Radford (2000) analysed elite athletes to investigate the kinetics of anaerobic metabolism and found results consisted of the measured running times and the computed measurements. The model used was able to accurately follow the time-distance history throughout the game like it was a 100 meters race. The results from this study provide strong support for the evidence and use of the three model equation of anaerobic metabolism thereby demonstrating that there are better models for proving the energy needs of athletes. Male elite sprinters exemplified several aspects of the kinetic energy release during intensive exercises. Sonderegger *et al*. (2016) further validated this claim by arguing that the performance of soccer players is positively related to high-intensity activities. The study also suggested that speed-endurance training was essential in enhancing the achievements of the competitive soccer player. Speed-endurance, according to Polglaze *et al*. (2016), can be explained as a form of near maximal or maximal intensity anaerobic training that could be categorised based on the allowed time for recovery between the performed sprints bouts. The primary aims of speed training are to make the athletes develop the ability to sustain their maximal sprints and high-intensity activities during matches for prolonged periods.

2.12: Conclusion

Metabolic power is not the 'panacea' of team-sport analysis, but it is a very useful tool. It provides a more comprehensive measure of intensity and volume for variable-speed locomotions, allowing for improved monitoring of training and competitions loads (Polglaze *et al*., 2019). Practitioners and researchers should choose the most relevant duration-specific period and microtechnology-derived variable for their specific needs to use these for the prescription of conditioning drills and training intensity (Whitehead *et al*., 2018). Nevertheless, experienced individuals are required to undertake the analysis to help further identify the peak match demands. Using microtechnology alongside video analysis, would provide coaches with more detailed information on the technical-tactical and physical demands during match-play.

In conclusion, MP and energy expenditure are essential constructs within modern day sports not only for the coaches and the athletes but also for the sports physicians and doctors. The amount of energy expended by an athlete has been found to be influenced by several factors including the intensity of the game, the level of the game (elite or lower level matches), and the extent of activities during a game such as high intensity running or a low concentration running. Therefore, the need to accurately measure the amount of energy expenditure has gained more significance over the past years. As a result, some processes have been developed to help regulate the energy demands and efforts during various games. Among the methods of measuring the performance of athletes to obtain data for calculating the energy, the use to multi-camera analysis, time-motion analysis, video motion analysis, and most importantly, the application of GPS are included. However, the validity and reliability of these techniques have been an ongoing issue of contention among different researchers and sports science technicians and scientists. Consequently, several experiments have been conducted to obtain the validity and reliability of these techniques. Although research on the use of GPS in sports has been extensive and comprehensive, much still needs to be done to obtain data required to calculate the energy demands of athletes in individual and team sports especially regarding the use of GPS as an analysis tool. The validity of these tools needs to be examined further to ensure their accuracy and improve the sports science support provided to athlete and coach.

Chapter 3: The validity of GPS to determine energy cost in elite soccer: general *vs.* sport-specific

3.1: Introduction

Soccer match play activity is characterised by repeated bouts of high-intensity running superimposed upon an aerobic background (Bangsbo *et al.,* 2006). Through the application of new technology, it has resulted in the evolution of performance analysis which now provides the most appropriate means to track, capture and analyse movement characteristics of intermittent team sports players (Tierney *et al*., 2016). This has been done through computer-aided tracking technology such as local position measurement technology and global positioning technology (GPS), allowing for assessment of training load to determine individual player performance profiles and ultimately design personalised and novel training approaches (Buchheit *et al*., 2014; Carling, 2013; Coutts *et al*., 2015; Hoppe *et al*., 2015). GPS studies that have been conducted in the literature have considered issues around the validity and reliability of GPS systems, performed using low-frequency GPS instruments (1-Hz and 5-Hz) and differ in reliability and validity compared to higher frequencies (see Table 2.3).

However, performance in team sports is rarely linear, and the ability to accelerate, decelerate and change direction at several ranges of speed and distance is critical to performance (Jennings *et al*., 2010; 2010a). Therefore, the validation of multidirectional and soccer-specific activities using high sampling frequency (10-Hz) GPS is crucial to obtain accurate representations of on pitch movement activities and to the evolution of metabolic power estimations. The use of laser measurement systems with a sampling frequency of ~100-Hz, would facilitate the accurate assessment of acceleration and deceleration phases of activities. A new low cost 10-Hz high-frequency GPS system (BT-1000ex, Qstarz, Taiwan) was used to conduct a comparison with a laser speed gun sampling at 100-Hz (LAVEG LDM-300c sport, Jenoptik AG, Jena, Germany) to validate the use of GPS measurement system.

In soccer, the ability to accelerate and/or decelerate during high-speed running with or without a change of direction (CoD) is plays a decisive role in the outcome of a game (Carling *et al*., 2008; Hader *et al*., 2016; Reilly *et al*., 2000; Taylor *et al*., 2017). It has been found that the capacity of players to repeatedly accelerate and decelerate plays a major role in their overall performance with the impact varying as a function playing position (Izzo & Lo Castro, 2005; Taylor *et al*., 2017), while incorporating other actions such as jumping, tackling, lateral shuffling and cutting (Bradley *et al*., 2010; Carling *et al*., 2008; Taylor *et al*., 2017). Athletes in endurance sports place a greater focus on generally linear steady-velocity submaximal and high intensity running (Laursen & Jenkins, 2002; Sloth *et al*., 2013). Both athletic populations express high levels of aerobic fitness but different specific metabolic adaptions in movement patterns.

Therefore, to gain a better understanding about sport specific demands further research is required to help quantify this (Taylor *et al.*, 2017). The determination of energy cost (C) for human movement has been assessed using numerous different methods within the literature (Arellano & Kram, 2014; Margaria *et al*., 1963), with the metabolic function related to any kind of sport locomotion mode at elite level, generally been evaluated in terms of maximum oxygen consumption [$\dot{V}O_{2max}$]. Presently, assessment of sport locomotion is done indirectly, through some sort of maximum aerobic power test, which has been found to be a relevant indicator in team sports. However, any specific training you wish to evaluate in terms of achieved locomotion economy needs a relevant C assessment. Colli *et al*. (2007) and Zadro *et al*. (2011) have indicated in the assessment of the shuttle-running C that the change of direction (CoD) phase plays critical role on the final value calculation of C.

Therefore, previous attempts made to assess the metabolic cost imposed by soccer match play and training through estimates of the metabolic load during match play activities calculated from energy cost paradigms that have derived from laboratory models of linear running are not relevant (Osgnach *et al*., 2010). In developing this indirect metabolic approach, the influence of playing surface on the metabolic power required during soccer has not been directly/empirically considered in the original metabolic equations (Minetti *et al.*, 2002). The energy cost of running on grass is assumed to be ~29% higher than that required on a treadmill with a coefficient of multiplication term of 1.29 (KT = 1.29) (Pinnington and Dawson, 2001). The incorporation of this into the algorithm of Osgnach *et al*. (2010) to account for the differences in energy cost presents a critical issue that likely impacts the accurate determination of the instantaneous energy cost of soccer specific activities (Stevens *et al*., 2015). The estimation of workload and energy expenditure of soccer training and match play nictitates the development of indirect methodologies to determine these parameters, by validation of sport-specific movements in soccer players.

The aim of this study was to first validate a GPS system to compare the speed and distance data measured by a gold standard laser technology system with a high-frequency 10-Hz GPS system and assess acceleration data by comparing the findings to quantify the work rate during intermittent linear and a-linear change of direction soccer specific tasks (Pilot study 1). Secondly, the next aim was to compare the different C of linear- and shuttle-running in elite athletes that possess high level of aerobic fitness but who are specifically adapted to either linear or shuttle/multidirectional running in their training and competition. Ultimately, these findings provided the basis of the present investigation set out to determine the energy cost of running on grass (C_r) in elite soccer players, via the incorporation of direct measures of oxygen cost taken on official UEFA standard grass playing surfaces.

3.2: Methods

3.2.1 Pilot Study 1

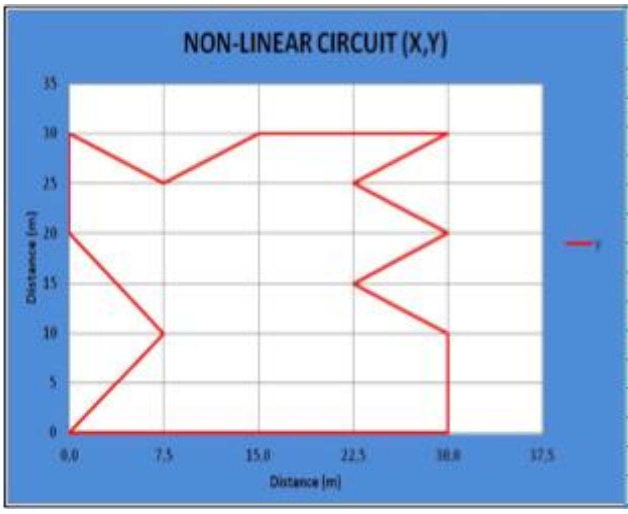
Participants

Ten male semi-professional soccer players playing at varsity level with age (mean ± SD) 21.0 ± 2.0 yrs, body mass 74.0 ± 5.0 kg, height 174.0 ± 6.0 cm were recruited for this study.

Research Design

Experimental design and protocol [GPS validation]

All participants were required in a random order to complete 4 different running conditions: 1-2) linear (straight)-line sub-maximal run over a marked 30 meters course with low-moderate acceleration and deceleration, 3-4) sub-maximal shuttle run over 20 meters keeping time with a sound signal to regulate running speed and 5) high-intensity accelerations and decelerations over 50 meters. Additionally, each participant undertook linear and change of direction tasks running several laps (6 laps) of a measured soccer specific circuit (Figure 3.1), which was set out on a synthetic sports surface. This was designed to simulate the kinematics velocity and changes of direction experienced during a soccer game. Seven days prior to the investigation, all participants undertook a habituation protocol to ensure familiarity. To facilitate participants adherence to the movement velocities and from accelerating/decelerating before a change in designated movement zones, cones were placed to designate the initiation and cessation point of the movement sequences. All protocol activities commenced from a stationary start position and required participants to come to a complete stop at the end of the marked course.



x	y	direction	angles (°)	distance (m)
0,0	0,0			
30,0	0,0	90	90	30,00
30,0	10,0	0	56	10,00
22,5	15,0	304	113	9,01
30,0	20,0	56	113	9,01
22,5	25,0	304	113	9,01
30,0	30,0	56	146	9,01
15,0	30,0	270	34	15,00
7,5	25,0	236	67	9,01
0,0	30,0	304	124	9,01
0,0	20,0	180	37	10,00
7,5	10,0	143	74	12,50
0,0	0,0	217		12,50
				total (m)
				144,08

Figure 3.1. Displacement, direction and angle of change during the non-linear soccer-specific circuit.

A metric trundle wheel with a counter was used to measure the exact length of the soccer-specific circuit and each participant familiarised with a sound signal emitted at set times to regulate running speed. During the non-linear circuit, an iPod system (iPod nano, Apple, Cupertino, California) was used to produce the pacing signals (a beep sound) every 5 seconds. As a spatial reference, multiple markers were positioned at fixed points depending on the running speed required. The running speed started at 2.5 m·s^{-1} and increased to 3.3 m·s^{-1} and 4.1 m·s^{-1} over two consecutive laps.

Movement of participants were tracked using GPS devices (BT-Q1000eX 10-Hz, Qstarz, Taipei, Taiwan; VX Log^{TM} 225, Visuallex Sport, Lower Hutt, New Zealand). During straight-line and linear shuttle running simultaneous measurement with a laser speed gun sampling at 100-Hz (LAVEG LDM-300c sport, Jenoptik AG, Jena, Germany), simultaneously, and performed to act as a gold standard. The measurement error for the laser speed gun concerning distance covered has been identified as being 0.10 ± 0.06 m over 100 m distance (Arsac & Locatelli, 2002) with a coefficient of variation of up to

0.2% over 10, 30, 50 and 70 metres (Harrison *et al.*, 2005). The laser speed gun was positioned behind the participants at the starting point of the linear runs and aligned with the centre of the participants back to ensure acquisition of laser signal, which is in accordance with the guidelines set by the manufacturers. Instantaneous velocity measurements were obtained for each trial. The GPS units were placed approximately 20 cm apart on the upper back in a custom-made vest on all participants. The mean ± SD number of satellites during data collection for both the linear (acceleration and deceleration) runs and the shuttle run were determined. Laser velocity data (100-Hz) was resampled to 10-Hz and 4-Hz for direct comparison with the respective GPS device and synchronised at the first movement recorded above 0 $m \cdot s^{-1}$ to account for processing phase delays inherent with GPS system. Data were downloaded and analysed using several commercial software related to each respective device (GPS Power, SPINItalia, Roma, Italy; LAVEG v3.9, Jenoptik, Jena, Germany; QSports v3.74, Qstarz, Taipei, Taiwan; VX View™, VX Sport, Lower Hutt, New Zealand) to determine the time, the speed and the distance, which was used for subsequent analysis.

Statistical analysis

All data were analysed using descriptive statistics. The results are presented as the mean ± the standard deviation throughout the text unless otherwise stated. The strength of association between individual laser (gold standard) and 10-Hz GPS estimates of running speed was assessed using Pearson (r) correlation analysis. The least squares regression approach was used to determine the validity of the 10-Hz GPS, where the laser estimates of running speed were regressed against each 10-Hz GPS calculated separately for each running speed (Batterham, 2004; Hopkins *et al.*, 2004; Hopkins, 2010). The potential for any fixed bias was assessed by determining whether the intercept for the regression was different from zero. To identify the presence of proportional bias, the slope of the regression line was assessed to determine if it was different from 1. The random error was quantified using the standard error of the estimate from the regression. As recommended by Bland & Altman (2003) and Hopkins *et al*. (2004), visual inspection of the residual plots (standardised residual on standardised predicted) was carried out to determine if the random error was uniform along the range of measures taken.

3.2.2: Pilot Study 2

Participants

Ten professional soccer players belonging to the second team of an Italian SERIE A club with age (mean ± SD) 17.6 ± 0.5 yrs, body mass 71.5 ± 6.8 kg, height 174.2 ± 6.1 cm, and maximal oxygen uptake ($\dot{V}O_{2max}$) 55.0 ± 3.6 ($mL \cdot kg^{-1} \cdot min^{-1}$), were recruited for group one of this study. A further seven marathon runners with age (mean ± SD) 33.4 ± 8.0 yrs, body mass 66.7 ± 7.1 kg, height 174.6 ± 6.2 cm, and ($\dot{V}O_{2max}$) 69.4 ± 3.7 ($mL \cdot kg^{-1} \cdot min^{-1}$), were recruited for group two of this study. Inclusion in the study required that the marathon runners had a mean best marathon time 2h30min.

Research design

Utilising a repeated measure design all participants attended the laboratory on four occasions initially to complete familiarisation with the protocols, then subsequently to complete a maximal oxygen uptake test, shuttle run test, and linear treadmill run. This experimental study was approached through an observational design. Each participant first completed a familiarisation session and thereafter each participant completed one experimental session (detailed below).

Measuring oxygen consumption and lactate concentration

Oxygen consumption was evaluated breath-by-breath using a portable gas analyser ($K4b^2$, Cosmed, Rome, Italy). The unit was previously calibrated according to manufacturer's instructions by means of a 3-L syringe and a gas mixture with similar values of what the subject breathes out (16.00% O_2 and 5.00% CO_2). During the tests, the gas analyser was placed with a harness on the subject's shoulders. Data were recorded by the unit and telemetrically sent to a personal computer. Results were reported as L-min averages and used for subsequent analysis. Peak blood lactate concentration ([La-]b) was measured by means of a portable analyser (Lactate Pro ™ LT-1710, Arkray Inc., Kyoto, Japan) in a blood micro sample taken from the subject's ear lobe 5 and 7 min after the end of the test. Oxygen consumption ($\dot{V}O_{2max}$ [$mL \cdot kg^{-1} \cdot min^{-1}$]) was measured during both straight- and shuttle-runs and lactate was measured after each run as well.

Energy cost of running

Straight-running (C_r)

For the calculation of C_r at different constant speeds, each participant ran at different constant speeds on a motorized treadmill (Excite Run 700i, Technogym, Gambettola, Italy) in order to identify anaerobic threshold speed, measure their steady-state $\dot{V}O_{2max}$ and run-end [La-]b. Each participant began with a 10-min 8 $km \cdot h^{-1}$ warm-up and then performed the test. Soccer players ran randomly at 10, 12, and 14 $km \cdot h^{-1}$, 5-min at each speed, and with 3-min rest between each run and then performed the next set. Marathoner runners' running speeds were 10, 14, and 17 $km \cdot h^{-1}$, respectively. The 10 and 14 $km \cdot h^{-1}$ speeds were chosen for subsequent energy cost of running (C_r) analysis. C_r was calculated as the above resting $\dot{V}O_{2max}$ – with the resting value assumed to be 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$ – divided by the speed in $m \cdot min^{-1}$ and therefore expressed in $J \cdot kg^{-1} \cdot m^{-1}$ (with the assumption of 1 mL O_2 = 20.9 J, i.e., considering a respiratory exchange ratio [RER] of 0.96).

Shuttle-running (C_{sh})

Each subject ran eight times four 22-m legs with three 180° CoDs per leg over 20-s (i.e., at 15.84 $km \cdot h^{-1}$ speed) with 20-s passive recovery between each run and the next one (i.e., 5-min total running plus recovery time) in addition to a further post-run 6-min recovery. Running speed was set by audio signals emitted by loudspeakers controlled by a personal computer. Energy cost of shuttle-running (C_{sh}) was calculated as the energy utilised above resting metabolism (E) in $J \cdot kg^{-1}$ divided by the distance in meters. E corresponds to the sum of the anaerobic alactic (AnAl), anaerobic lactic (AnL) and aerobic contributions (Aer). The anaerobic alactic contribution was calculated by taking into account the kinetics during the recovery. The recovery area under the linear interpolation from the 4^{th} to 6^{th} min values provides an estimate of the oxygen required to re-pay the anaerobic alactic contribution (di Prampero *et al.*, 1973; 1999) (Figure 3.2). The anaerobic lactic contribution was calculated by multiplying [La-]b above the resting value, assumed to amount to 1 mM, by 3 $mL \cdot kg^{-1}$ O_2 (di Prampero *et al.*, 1981). The aerobic contribution was calculated as the measured over the 5-min total running plus recovery time, above the resting value, assumed to amount to 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$. C was expressed in $J \cdot kg^{-1} \cdot m^{-1}$ (with the assumption of 1 mL O_2 = 20.9 J, i.e., considering a respiratory quotient of 0.96).

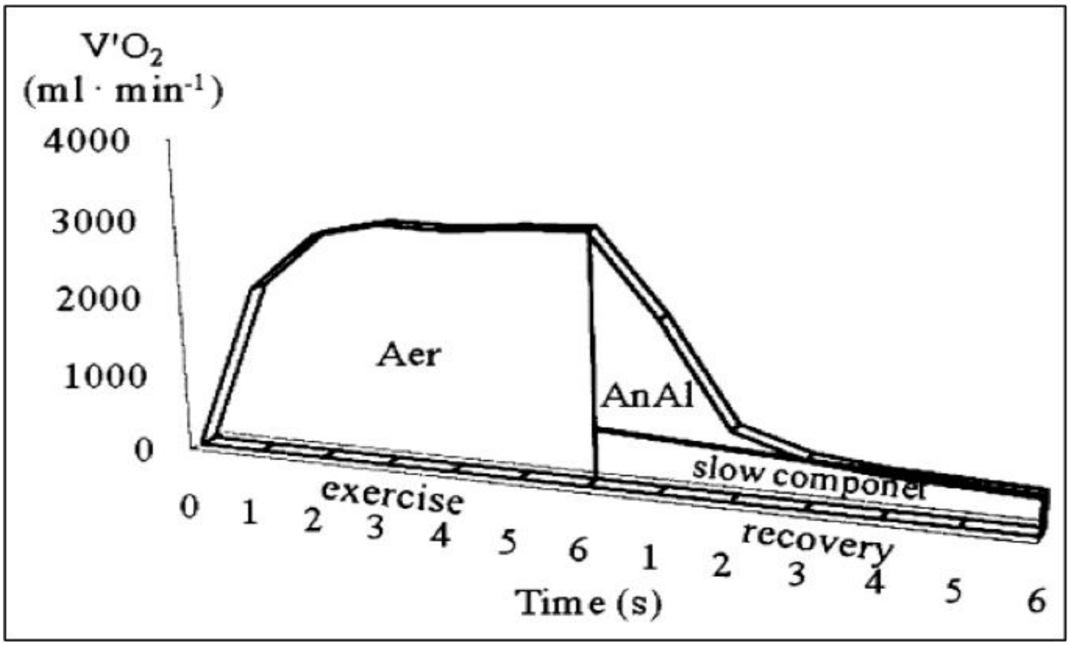


Figure 3.2. Typical oxygen consumption ($\dot{V}O_2$) above-resting value kinetics over a hypothetical 6-min exercise plus 6-min recovery (reproduced after di Prampero, 1981).

Statistical analysis

All data were analysed using Statistical Package for the Social Sciences version 22 for Windows (SPSS, Chicago, IL, USA). All data were checked for normality using the Shapiro-Wilk test. Differences between groups were evaluated using an independent t-test. The results are presented as the mean ± the standard deviation throughout the text unless otherwise stated. The alpha level of significance was set at 5% (Kinear & Gray, 1995).

3.2.3: Main study

Participants

Seventeen male elite, professional soccer players of a national and international level (age [mean ± SD] 24.0 ± 2.9 years, stature 175.1 ± 4.9 cm, and body mass 75.9 ± 5.2 kg) were recruited for this study. Verbal explanation of the experimental procedure was provided to everyone; this included the aims of the study, the possible risks associated with participation and the experimental procedures to be utilised. The experimental procedures were approved by the local Human Ethics Committee. Participants were required to avoid all alcohol 24 h prior to each test. None of the participants presented with a history of bone fractures and/or a history of musculoskeletal abnormality; and none of the participants were receiving any pharmacological treatment during this study. All participants gave their written informed consent. The study was conducted in accordance with the ethical standards of the journal and complied with the Declaration of Helsinki.

Experimental protocol

Each participant completed two sessions each attendance separated by at least 3 days. The participants first underwent an assessment of oxygen consumption ($\dot{V}O_2$) at rest followed by an incremental treadmill run to exhaustion to assess $\dot{V}O_{2max}$. $\dot{V}O_2$ was assessed by means of a portable breath-by-breath Cosmed K4b^2 gas analyser (Cosmed, Rome, Italy). On a second occasion, each participant performed a run on an UEFA standard grass soccer pitch with soccer shoes to evaluate C_r. The participants were free to live a 'normal life' between sessions, sleeping at home at night and attending lectures and doing light office work in the day. They were told to refrain from drinking alcoholic or caffeinated beverages and from other training or heavy exertion for the 48 h before the experiments or during them. Participants body mass was assessed to the nearest 0.1 kg using a Seca weighing scales (Seca, model 702, Germany), and height, to the nearest 0.1 m, using the Seca stadiometer (Seca, model 217, Germany) during the initial visit.

Maximum oxygen consumption ($\dot{V}O_{2max}$) assessment

The protocol started at a speed of 8 km·h^{-1}, with the speed increasing by 2 km·h^{-1} every 2 min up to a maximal speed of 16 km·h^{-1}. Once the maximal speed was achieved, thereafter the gradient was increased by 2.5% every 2 min until volitional exhaustion. $\dot{V}O_2$ and heart rate were measured continuously on a 5-sec basis. $\dot{V}O_{2max}$ was identified as the highest value of each at volitional exhaustion (Beltz *et al.,* 2016).

Straight-running energy cost (C_r) assessment

Straight-running energy cost assessment was performed on a UEFA standard grass soccer pitch (Artemio Franchi stadium, ACF Fiorentina, Florence, Italy) and required all players to wear soccer shoes. All participants were asked to perform an aerobic-based 10.29 km·h^{-1}, 6-min, steady-state, circular run (Figure 3.3). Each run's path was marked with cones every 20 meters with each participant controlling his speed by paying attention to a PC-controlled sound signal emitted every 7 sec (i.e., sound every 20 m and 7 sec, that means 10.29 km·h^{-1} speed respected). Each subject was instrumented to wear a wrist heart rate monitor (RS800sd, Polar Electro Oy, Kempele, Finland). $\dot{V}O_2$ was measured on a breath-by-breath basis using a portable metabograph (K4b^2, Cosmed, Rome, Italy). In accordance with the manufacturer's instructions, the portable unit was calibrated for flow measures using a 3-L syringe and for gas percentage measures by using a gas mixture of known composition (i.e., 16.00% O_2 and 5.00% CO_2 in N_2). During the straight-running test, the portable unit was kept in a harness on the participant's shoulders. Data were recorded locally by the portable unit and sent telemetrically to a PC. $\dot{V}O_2$ data were averaged over 1-min epochs. Steady-state $\dot{V}O_2$ was defined as the mean of the last three min of the straight-running test. Before the start of the study, all participants were fully familiarised with the instruments and procedures.

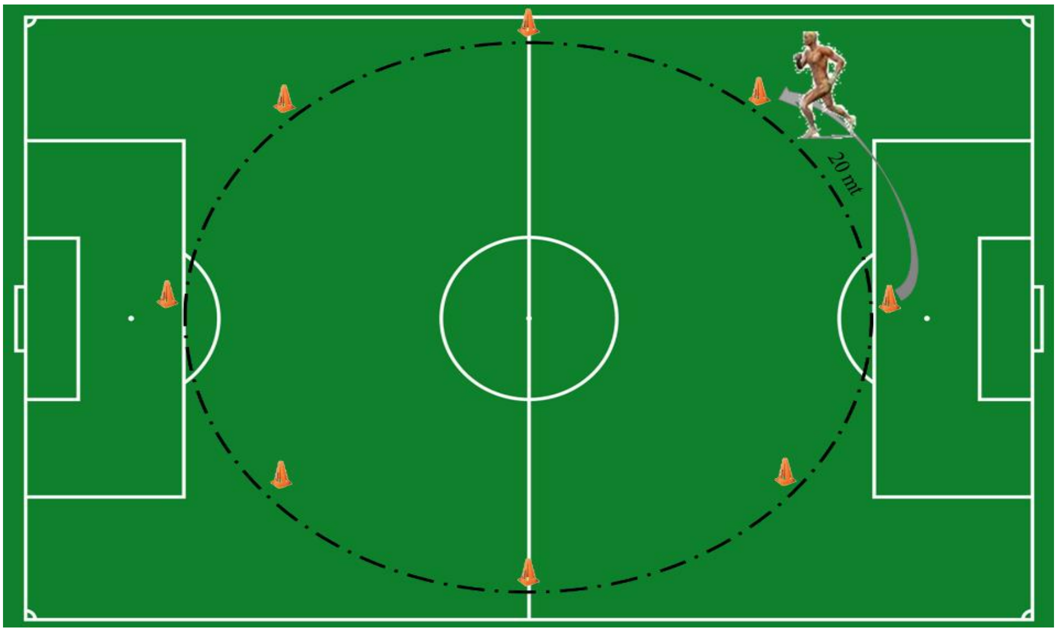


Figure 3.3. Illustration of the UEFA standard grass soccer pitch; the spatial markers show the circular path of the test.

Energy cost of running (C_r) calculation

C_r was calculated as the ratio between $\dot{V}O_2$ above its resting value ($\dot{V}O_{2n}$) and the speed (v):

$$C_r = \dot{V}O_{2n} / v$$

assuming an energy equivalent of 20.9 J *per* mL of O_2 (corresponding to a non-protein respiratory exchange ratio of 0.96) and v is 10.29 km·h^{-1} (i.e., 2.86 m·s^{-1}), a speed below the anaerobic threshold one. When a steady-state exercise is performed below the anaerobic threshold intensity, all the metabolic energy demand is satisfied by means of the aerobic energy mechanism. C_r resulted therefore expressed in J·kg^{-1}·m^{-1}.

3.3: Results

Pilot Study 1:

During all completed trials the mean number of satellites (± SD) acquired during data collection for the linear task (acceleration and deceleration) and the shuttle run was 10.77 ± 0.85 compared to 10.60 ± 0.90 during the circuit. The mean horizontal dilution of position (HDOP) during data collection was 0.89 ± 0.10 for linear acceleration and decelerations, and the shuttle run and 0.88 ± 0.08 for the soccer-specific circuit.

Figure 3.4 presents the typical response to a linear acceleration and deceleration task across all GPS systems (n = 4). It was established that the trend of speed was acceptable in both the 4-Hz and 10-Hz GPS systems. However, the ability to track changes in acceleration and deceleration of the 4-Hz GPS was poorer than the 10-Hz device which showed a greater accuracy. Furthermore, the 4-Hz GPS device showed a loss of accuracy even when speed remained constant.

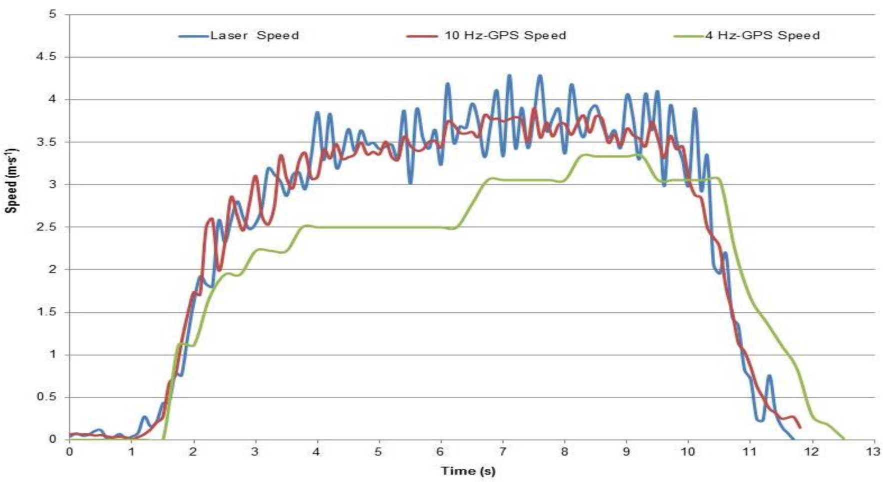


Figure 3.4. Comparison of the typical running speed response curve for 10-Hz GPS *vs*. 4-Hz GPS *vs*. laser during linear acceleration and decelerations over 30-m at moderate intensity. The red line indicates the 10-Hz GPS, the green line highlights the 4 Hz-GPS and the blue line the laser speed gun.

During each linear run consisting of 20, 30 and 50-m of acceleration and deceleration it was found that mean ± the standard deviation of the laser system derived relative in relation to 10-Hz GPS derived distance covered respectively for the different running speeds was: 30.33 ± 0.77 m *vs*. 29.50 ± 0.87 m (-0.027%) at 2.5 $m \cdot s^{-1}$; 30.22 ± 0.91 m *vs*. 29.45 ± 0.98 m (-0.025%) at 3.3 $m \cdot s^{-1}$; 50.47 ± 0.40 m *vs*. 49.27 ± 0.84 m (-0.024%) at 4.38 $m \cdot s^{-1}$ and 39.26 ± 0.52 m *vs*. 38.55 ± 0.46 m (0.018%) during shuttle running.

The GPS system underestimated the distance covered for all activities. The measurements collected from the soccer-specific circuit (non-linear) showed that total distance covered, as measured by the 10-Hz GPS, compared to the actual measured distance was 140.84 ± 2.27 m, (-2.25%) at a speed of 2.5 $m \cdot s^{-1}$, 136.01 ± 3.69 (-5.6%) at a speed of 3.33 $m \cdot s^{-1}$ and 138.8 ± 2.38 m (-3.67%) at a speed of 4.16 $m \cdot s^{-1}$. As displayed by Figure 3.5, the 10-Hz GPS clearly underestimates the criterion of distance during the soccer-specific circuit.

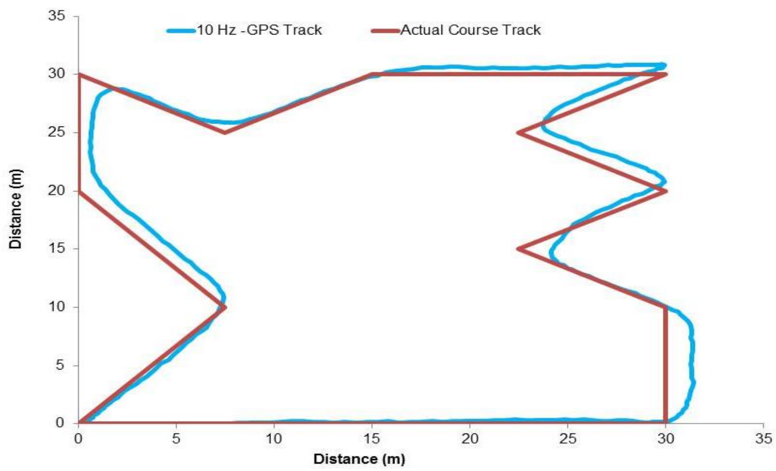


Figure 3.5. Comparison of the actual distance covered, and the estimation of distance covered through the 10-Hz GPS through comparison of the transit path during the linear and non-linear soccer-specific circuit at a speed of 3.33 $m \cdot s^{-1}$.

The slopes, intercepts and the standard error of estimates (SEE) are presented in Table 3.1. It was found that the random error was relatively similar across the different movement tasks with the smallest value being 0.018 $m \cdot s^{-1}$ for the low-intensity run and further augmented to 0.070 $m \cdot s^{-1}$ when the speeds increased a change of direction was incorporated. Through assessment by visual inspection of the regression line (Figure 3.6), a potential for bias was assessed.

Table 3.1. Least squares regression analysis (R) of the slopes, intercepts, standard error of estimate (SEE) and 95% confidence interval (95% CI) between the laser gun and 10-Hz GPS for various running speeds ($m \cdot s^{-1}$) and metabolic power ($W \cdot kg^{-1}$) in varsity soccer player.

Running Speed	10-Hz Laser ($m \cdot s^{-1}$) Mean ± SD	10-Hz GPS ($m \cdot s^{-1}$) Mean ± SD	Laser–GPS Δ ($m \cdot s^{-1}$) Mean ± SD	% Diff	Slope	Intercept	SEE	R
Low Intensity	2.15 ± 0.6	2.10 ± 0.60	0.062 ± 0.01	-2.9	0.93 (0.75-1.31)	0.14 (-0.138 - 0.51)	0.018	0.98
Moderate Intensity	3.29 ± 1.3	3.20 ± 1.3	0.095 ± 0.05	-2.9	1.11 (0.88-1.34)	0.269 (-1.01 - 0.48)	0.052	0.96
50-m linear Acc/Dec	3.98 ± 1.8	3.86 ± 1.81	0.11 ± 0.07	-2.9	0.88 (0.73-1.04)	0.560 (-0.04 - 1.16)	0.067	0.97
20 MST linear with 180° CoD	3.40 ± 1.4	3.31 ± 1.4	0.08 ± 0.07	-2.5	0.80 (0.36-1.25)	0.729 (-0.75- 2.21)	0.074	0.82
Metabolic Power 20-m sub-max ($W \cdot kg^{-1}$)	23.26 ± 0.3	22.79 ± 0.3	0.47 ± 0.07	-2.1	-	-	-	-
Metabolic Power 20-m max sprint ($W \cdot kg^{-1}$)	32.17 ± 2.5	31.84 ± 2.4	0.33 ± 0.11	-1.1	0.998 (0.96-1.01)	0.737 (0.90 – 1.38)	0.239	0.99

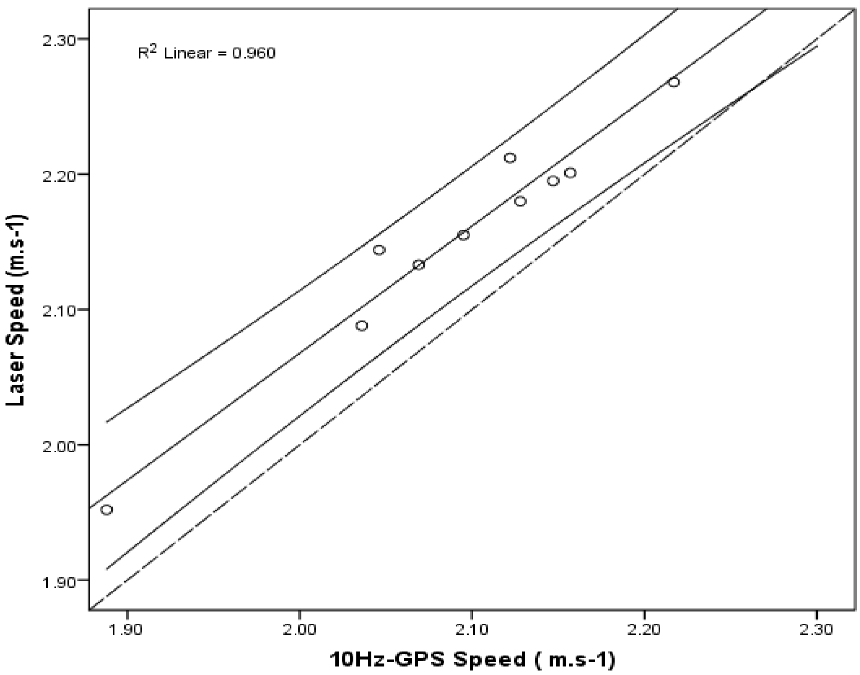


Figure 3.6. Least Squares regression analysis plot (R) of the slopes, intercepts, standard error of estimate (SEE) and 95% confidence interval (95% CI) between the laser gun and the 10-Hz GPS for low intensity running speeds ($m \cdot s^{-1}$) in varsity soccer players. (Note the underestimation of speed as indicated by the points lying above the line of unity [broken line] indicate a fixed bias. The example illustrated suggests that relative to the laser gun it underestimates speed by a margin of -0.06 $m \cdot s^{-1}$, in conjunction with a small SEE 0.018 $m \cdot s^{-1}$).

Pilot Study 2:

Linear-running [La-]b values are shown in Table 3.2. Conversely to walking, it is widely accepted that the metabolic rate during running increases linearly as a function of the speed. Thus, it has been proposed that C_r is independent from the running speed (di Prampero *et al*., 1986; 2009; Giovanelli *et al*., 2015; Margaria *et al*., 1963). Compared with marathoners, soccer players C_r was approximately 7.2% higher (P = 0.046), whereas their C_{sh} was 10.9% lower (P = 0.002, Table 3.3).

Table 3.2. Mean (± SD) values for peak blood lactate concentrations (mmol·L^{-1}) over different speeds in soccer players and marathon runners.

Speed (km·h^{-1})	Soccer players	Marathoners
10	1.3 ± 0.1	1.0 ± 0.1
12	2.1 ± 0.2	-
14	3.7 ± 0.3	1.9 ± 0.2
17	n/a	4.8 ± 0.1

Table 3.3. Mean (± SD) values for energy cost (J·kg^{-1}·m^{-1}) in linear (C_r)- and shuttle-running (C_{sh}) for soccer players and marathon runners. Statistical significance (P < 0.05) is indicated in bold. *Different than soccer players.

Running type	Soccer players	Marathoners	Δ%	*P* value
Linear-running	4.3 ± 0.4	4.0 ± 0.2*	+7.2	***0.046***
Shuttle-running	7.4 ± 0.2	8.3 ± 0.4*	-10.9	***0.002***

Main Study:

$\dot{V}O_{2max}$ and C_r resulted in 55.7 ± 3.4 mL·min^{-1}·kg^{-1} and 4.66 J·kg^{-1}·m^{-1}, respectively. All the relevant bioenergetics values are showed in Table 3.4.

Table 3.4. Mean (± SD) values for the bioenergetics variables in 17 elite soccer players.

Bioenergetics variables	**Mean ± SD**
$\dot{V}O_{2max}$ (mL·kg^{-1}·min^{-1})	55.7 ± 3.4
Rest $\dot{V}O_2$ (mL·min^{-1})	266.0 ± 18.0
Steady-state running $\dot{V}O_2$ (L·min^{-1})	2.9 ± 0.3
Steady-state running $\dot{V}O_2$ (mL·kg^{-1}·min^{-1})	40.8 ± 3.0
C_r (J·kg^{-1}·m^{-1})	4.66 ± 0.4

3.4: Discussion

The first pilot study found that both 10-Hz and 4-Hz GPS devices are valid tools for measuring distances covered, running speed and accelerations during intermittent running activity consistent with that reported using 5-Hz GPS in simulated intermittent activity protocols (Coutts and Duffield, 2010; Petersen *et al*., 2009). The findings indicate that the current 10-Hz GPS system is like other commercially available systems and offers acceptable accuracy in multidirectional movements. As with similar systems when running speed increases accuracy seems to decline although the magnitude of this decline is attenuated with higher 10-Hz GPS frequency. The use of a higher sampling rate of 5-Hz allows for more accurate data representing short high-speed movements (Jennings *et al*., 2010; Portas *et al*., 2010). The findings from this research further support the general notion that doubling sampling rate from 5-Hz to 10-Hz improved the accuracy of running speed and distance travelled measurements and is in line with previous observations (Castellano *et al*., 2011a; Varley *et al*., 2012), with 4-Hz GPS proving impractical in this setting.

There was a disassociation between the 4-Hz GPS and both the laser system and the 10-Hz GPS in its ability to track acceleration, constant velocity and deceleration over short distances. Figure 3.7 shows the typical responses of the 10-Hz GPS during the acceleration and declaration phases. The 10-Hz GPS and the laser system can track accelerations and decelerations accurately. Further, the small error rates of less than 4% between both systems as derived for the criterion of speed values, would most likely not be enough to affect the assessment and/or classification of movement or metabolic cost during game activities, when translating these findings to a game specific context. However, it is important to note that the presence of fixed bias indicates that the 10-Hz GPS slightly underestimates running speed when compared to the laser system for all tested velocities. This finding is consistent with other reports sampling GPS at a lower frequency and may reflect the satellite offsets pre-built into the systems.

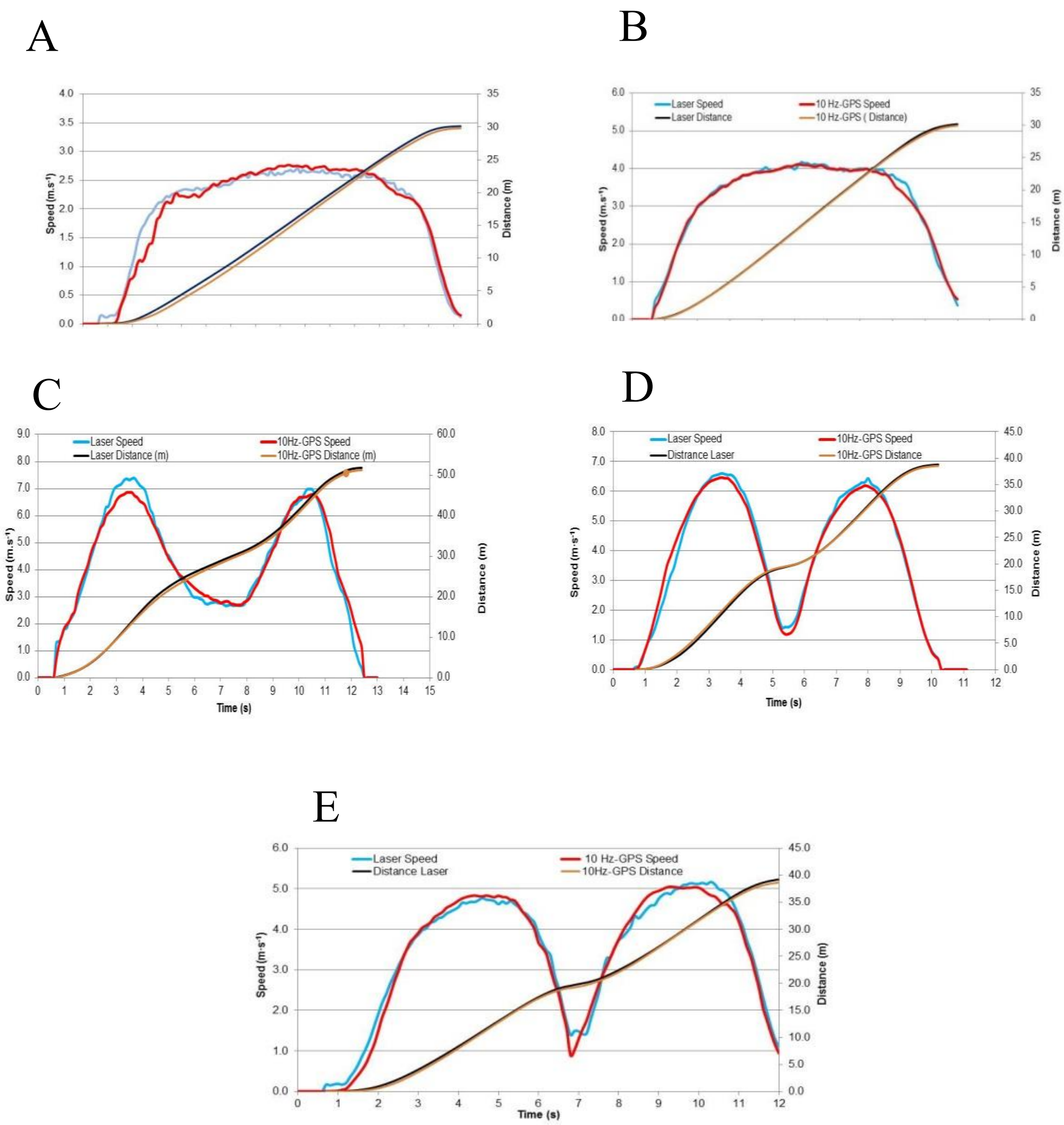


Figure 3.7. A comparison of typical running speed and distance measures derived from a 10-Hz GPS relative to laser during linear acceleration and decelerations at low intensity over 30-m (Panel-A), moderate intensity over 30-m (Panel-B), and high intensity over 50-m (Panel-C). Panel D and E show a shuttle-run over 40-m (20+20 m) at two different intensities.

The present data showed that when speed increased, the accuracy of the measure was maintained during both linear and change of direction tasks with the 10-Hz system. The maintenance of tracking accuracy with 10-Hz GPS during shuttle running tasks with a 180º change of direction disagrees with the findings of Portas *et al*. (2010). They suggested that 5-Hz systems are not accurate in measuring data from a soccer-specific task, such as movements with a broad range of change of direction. Nevertheless, the data acquired during the first pilot study indicated that a 10-Hz sampling frequency provides an underestimation of running speed and distance of more than 4% in shuttle-run tasks at various speeds with 180º change of direction.

The quality and accuracy of the GPS signal, we reported the satellite lock and the Horizontal Dilution of Precision (HDOP) which can be considered the sum of all the errors that may impact upon GPS signal quality (Witte and Wilson, 2004). The main factors influencing HDOP are the number of visible satellites and their position around the receiver unit (Williams and Morgan, 2009). Values range from 1-50 with 1 indicating ideal scenarios where a satellite is locked directly overhead with others providing a systematic array spread equidistant around the horizon. Variation from this suggests increasing unreliability (Witte and Wilson, 2004). Satellite lock and HDOP are critical aspects of information and should be reported during the data collection process for all future work. Any data collected with less than five satellites lock and an HDOP of greater than 2.5 should be considered inaccurate and should be avoided (Hewitt *et al*., 2012; unpublished data LJMU Soccer Exchange). The current work indicated that during linear accelerations/decelerations and non-linear soccer-specific circuits there was an average satellite lock of 10.77 ± 0.85 and 10.60 ± 0.90 with an average HDOP of 0.89 ± 0.10 and 0.88 ± 0.08, respectively. These findings are within the recommended requirements regarding satellite lock and HDOP and can therefore be considered acceptable.

The main findings in the second pilot study established that the determination of energy cost derives from a purely physiological component and specific technique. Improving C and thinking that efficiency is the same in any type of movement during training is a methodological error. All athletes, like the marathon runners and soccer players used in this study, have different goals and objectives of training which are based on energy demands related to their competition considering all the specificities that are needed to excel. If the aim of a marathon runner is to improve his running economy, through increasing his $\dot{V}O_{2max}$, only small improvements can be made if he is an advanced athlete and this will not be improved beyond the normal circannual oscillations. However, for a soccer player to become more efficient in the straight-line running it would mean spending a lot of time training a technique that has nothing to do with the biomechanics of ball control or the need to accelerate and decelerate suddenly and intermittently as required to do so in soccer. Therefore, the importance of considering the nature and needs of the sport is vital and influences the energy cost of movement.

The main finding of this main study was that in elite professional soccer players, the energy cost of linear-running (C_r) on a UEFA standard grass soccer pitch is 4.66 $J \cdot kg^{-1} \cdot m^{-1}$. Constant-speed linear-running measured oxygen consumption amounted to 73% of maximum oxygen consumption, confirming the aerobic nature of the metabolic demand due to the set C_r assessment speed. Pinnington and Dawson (2001), and Rodio *et al*. (2004) have reported values of 4.64 and 5.7 $J \cdot kg^{-1} \cdot m^{-1}$ when running on natural grass in a group of recreational runners and sedentary males, respectively. In a group of amateur soccer players, Sassi *et al*. (2011) reported a C_r value of 4.2 $J \cdot kg^{-1} \cdot m^{-1}$, which is lower than the present value. More recently, Stevens *et al*. (2015) in a group of non-elite players determined C_r to be approximately 4.6 $J \cdot kg^{-1} \cdot m^{-1}$ at a running speed of 10 $km \cdot h^{-1}$ on artificial turf. It can be thus be established that on grass and turf, C_r assessment provide different estimates of C_r, which seem to vary as a function of the surface type as well as the assessed population. Present results are clearly different from Sassi *et al.* (2011) i.e., C_r does not exceed 4.5 $J{\cdot}kg^{-1}{\cdot}m^{-1}$. It is believed this difference may be due to the study surface type and the assessed population, in addition to the fact that our participants wore soccer shoes. The integration of these factors together may affect running kinematics and in doing so increasing the metabolic demand (Dolci *et al.*, 2018). It should also be remembered that the C_r presented herein reflect a non-fatigued player with replete muscle glycogen concentrations. It remains to be determined if the C_r changes as a function of fatigue related changes in metabolic, cardiorespiratory, biomechanical, and neuromuscular efficiency fluctuations during a match-play and training thus current measures should be considered with this caveat in mind.

3.5: Conclusion

In conclusion, it can be established that through comparison between different measuring systems an increased GPS sample frequency (rate) provides a valid means of assessing running speed during rapid acceleration and deceleration that occur during linear runs and runs with tight changes of direction relative to a 100-Hz laser system. Further, the determination of energy cost derives from a purely physiological component and specific technique and is dependent on the nature of the sport of the athlete. Most importantly, assessment of the C_r profile over the season has shown that such a bioenergetics variable increases from the start to the end of the soccer matches' calendar (Buglione & di Prampero, 2012). Such a finding, yet to be confirmed, prompts further research towards the study of both straight- and shuttle-running on natural grass pitches C_r in elite soccer players. Given that these players might have developed a high-level specialization in running with frequent accelerations, decelerations, and changes of direction, coaches and players need to pay special attention to the monitoring and possibly conditioning of this kind of C_r, as well. This study provided an up-to-date measure of on-pitch C_r. Such a value is only slightly higher (+0.4%) than the one proposed by Pinnington and Dawson, (2001) commonly used as equation constant term (Minetti *et al.*, 2002) within the so-called "metabolic power" approach (Osgnach *et al.*, 2010). Yet, it is based on present data advisable to start using the new estimate presented here in given that – differently from the current one – it is a result from an investigation on elite soccer players rather than an extrapolation from a recreational non-elite population undertaking activity on a non-elite soccer standard surface.

Link between Chapter 3 to Chapter 4:

Taking advantage of the help of technology in modern sports, allows practitioners to better evaluate and plan workouts according to a performance model. The application of validated tools can support the measurement of physical and physiological parameters. Studying the energy cost of running in its sport-specific variants helps us to better understand the fundamental value of the technique, and the variables that emphasise the qualities of an athlete. The possibility of calculating this parameter of movement efficiency in soccer can offer an important starting point for improving the energetic equations currently used in the concept of metabolic power.

Chapter 4: Validity of a new metabolic power algorithm based upon di Prampero's theoretical model of energy cost

4.1: Introduction

To monitor C_r, it is important to understand several factors that influence the accuracy of C_r determination. The original concepts (di Prampero *et al.*, 2005; Minetti *et al.*, 2002) were based on running on compact terrain (like treadmills) and recent findings have established that running on a grass surface elevates C_r by ~30% when compared to running on dense terrain (Pinnigton & Dawson, 2001). Further, fitness level influences C_r as running economy can easily be improved through training (Beneke & Hütler, 2005; Iaia *et al*., 2009), with research on professional soccer players showing that C_r of running increased by 14% from pre-season to in-season (Buglione & di Prampero, 2012). As a result, Osgnach *et al*. (2010) based their equation on the work conducted by Minetti *et al*. (2002) and added the Pinnington and Dawson (2001) correction, which consists of a multiplication term of 1.29 (KT = 1.29) to consider the difference between running on a treadmill and on a grass pitch. However, the incorporation of this multiplication term into Osgnach's model presents a critical issue that impacts the accurate determination of the energy cost of soccer-specific activities. Pinnington and Dawson (2001) developed KT through analysis of recreational runners which does not present a suitable kinematic model of running that is representative of elite soccer players. Therefore, there is a need to re-establish the coefficient of multiplication as this may not provide an accurate representation of the metabolic constant in soccer players. In addition, Osgnach *et al*. (2010), failed to reflect the accurate energy cost imposed by running on a grass surface and did not use a population of elite athletes, meaning the estimation of the metabolic power could be impaired and inaccurate.

Buchheit & Simpson (2016) have discussed the difference between the direct measure of metabolic power (P_{VO2}) and the approach derived and proposed by Osgnach *et al.* (2010). Arising from those considerations, several limitations that may contribute to the underestimation of P_{GPS} noted, including the sampling frequency of GPS and the mathematical treatment of speed data (Stevens *et al.*, 2014), the method used for the calculation of the MP in an intermittent submaximal exercise (Buchheit *et al.*, 2015a). In addition, the experimental design of the work protocol failed to population specificity (e.g. elite soccer players) and variances in C across different playing surfaces (e.g. natural grass). Further, the performance assessment model undertaken work:rest ratio and different movements-activities (e.g. sprint, running, jogging, walking *etc*.) as well as the presence of the ball corrected from the temporal point of view in the chosen exercise (Buchheit *et al.*, 2015a; Brown *et al.*, 2016) need to be considered. Active and passive pause/recoveries play a central role, together with the choice of the analysed sport in determination of P_{GPS} (Highton *et al.*, 2016).

Following di Prampero's approach and the concept of metabolic power in soccer, the goal is to determine - by developing specific runs in a non-linear test - the difference between the direct measurement of oxygen consumption through a portable metabolic device ($P_{\dot{V}O2}$) and the indirect measurement through GPS (P_{GPS}, metabolic power from GPS), to validate this procedure deemed useful for analysing soccer activities during match-play and training sessions.

It has been found that: the statistical approach for comparing two methods of measurement is contentious. Bland and Altman's 95% limits of agreement is the most commonly adopted approach for method comparison. The differences between the two methods of measurements taken on the same participants are determined by the mean of these differences. However, this approach has been criticised by Ludbrook (1997; 2010) and Hopkins (2004) about how potential bias between the two methods is determined. Ludbrook (1997; 2002) illustrated that the 95% limits of agreement did not always appropriately distinguish between fixed and proportional bias. Fixed bias occurs when the values of one method of measurement are either higher or lower than the other method of measurement by a constant amount, whereas proportional bias is when the size of the difference between the values for the two methods of measurement is related to the size of the value being measured (Ludbrook, 1997; 2002). Therefore, it is important to understand that there can be different goals in method comparison and that Bland and Altman's approach was initially designed to determine if two methods can be used interchangeably. Bland and Altman (1986) state that their approach is not for situations where the values of a new method are compared to the values of a highly accurate measure (i.e., calibration). Instead, it is for use in situations where the goal is to determine if a new method of measurement has enough agreement with an old method of measurement such that the old method could be replaced.

Both Hopkins (2004) and Ludbrook (1997; 2010) have argued that using the limits of agreement is inappropriate for situations of calibration, where a new method is to be compared to a gold standard (i.e., criterion validity). In the Bland and Altman approach the differences between each participants' scores on the two methods of measurement are plotted against the averages of the participants' two scores. Therefore, Ludbrook (1997; 2002; 2010a) recommends the use least products regression in calibration studies as it appropriately identifies whether fixed and/or proportional bias is present between a potential new method of measurement and an established gold standard. Fixed bias would occur when the values of a new method of measurement are either higher or lower than the gold standard's values by a constant amount, whereas proportional bias occurs when the size of the new method value that is over or under the gold standard is proportional to the size of the value being measured (Ludbrook, 1997; 2002). All measurement tools/processes contain error. Therefore, a gold standard measurement tool and the potential new method will both contain random error in their values. Least squares regression assumes that whichever method of measurement is the independent variable.

The aim of this study was to validate a new equation that considers these factors on the energy cost of running on UEFA standard grass playing surfaces (C_r) in elite soccer players, during a soccer specific intermittent movement protocol relative to directly determined physiological data using a new statistical approach. This will be done through the information determined from previous chapters and incorporating these into a new metabolic power algorithm that includes specific energy cost terms developed in elite players population, developed upon a normal playing surface, with soccer-appropriate footwear to best replicate factors important in the determination of movement economy and thus energy cost.

4.2: Methods

Participants

Thirteen male elite, professional Serie A soccer players of a national and international level with age (mean ± SD) 22.1 ± 5.9 yr, height 181.8 ± 5.4 cm and body mass 76.5 ± 6.2 kg took part in this study. All players had at least ten years of experience playing in national championships from a junior age. Verbal explanation of the experimental procedure was provided; this included the aims of the study, the possible risks associated with participation and the experimental procedures to be utilised. The experimental procedures were approved by the local Human Ethics Committee of Liverpool John Moores University. The study complied with the Declaration of Helsinki.

Research Design

Prior to the main experiment, all players underwent a soccer-specific intermittent exercise protocol on several occasions to familiarise and facilitate subsequent physiological data collection. During each trial, participants were fitted with a 10-Hz GPS unit (BT-Q1000eX 10-Hz, Qstarz, Taipei, Taiwan), and a portable gas analyser (K4b^2 Cosmed, Rome, Italy), to assess the oxygen uptake directly. At the start and end of each testing session, blood lactate was collected via a portable lactate analyser (Lactate Pro ^{TM} LT-1710, Arkray Inc., Kyoto, Japan).

New energy cost equation (Minetti modified) calculation

The new energy cost equation modified according to Minetti (2002), was derived from findings in Chapter 3, using the Pearson correlation coefficient modelling of energy cost directly measured on a UEFA standard natural grass soccer surface while wearing soccer boots. An C_r value of 4.66 J·kg^{-1}·min^{-1} was established using several curves fit models from a 2nd to a 4th order polynomial fit (Figure 4.1). The determination of this new energy cost as the constant term is central to the identification of 'Metabolic Power' in soccer and further enhances previous models by providing both a surface specific and population specific energy constant. The previous constant of 3.6 $J \cdot kg^{-1} \cdot min^{-1}$ was altered to reflect the true energy cost of running on UEFA standard natural grass pitch in elite players. The new constant modifies and disrupts the essential mathematical slope and shape of the Minetti *et al*. (2002) model ranging from -45% to 45% and impairs the calculation of metabolic power. To maintain the integrity of the equation in this range (-45% to 45%) while correcting for the underestimation of energy cost that it is created during decelerations (gradients) greater than -45% modification of the slope (% gradient)/energy cost data with a different model was used. Following the mathematical model of di Prampero *et al*. (2005), fitting acquired data (in Chapter 3) with a 4^{th} order polynomial (Figure 4.1) meets the requirements of the equation. The constant term of the energy cost is held at 4.66 $J \cdot kg^{-1} \cdot m^{-1}$, and the error term is minimised (0.12 $J \cdot kg^{-1} \cdot m^{-1}$) more efficiently than either a cubic or parabolic model. Decreasing the order of the polynomial fit for the equation to both a 2^{nd} and 3^{rd} order (2°-3° degree) translates the trend line, shifting it upwards on the y-axis, in effect overestimating the directly determined constant term from 4.66 to 4.79 $J \cdot kg^{-1} \cdot m^{-1}$. The new 'Energy Cost equation' was thus raised to the fourth-degree polynomial. In doing so it does the following: a) remove the negative inflexion point associated with deceleration activity over a -45% gradient apparent in the original Minetti *et al*. (2002) model; b) the energy cost of the constant speed running remains comparable to that directly measured in the 17 elite soccer players (in Chapter 3) on a UEFA standard natural grass pitch (Artemio Franchi Stadium, Florence, Italy). The new equation value of 4.66 $J \cdot kg^{-1} \cdot m^{-1}$ was used for subsequent analysis.

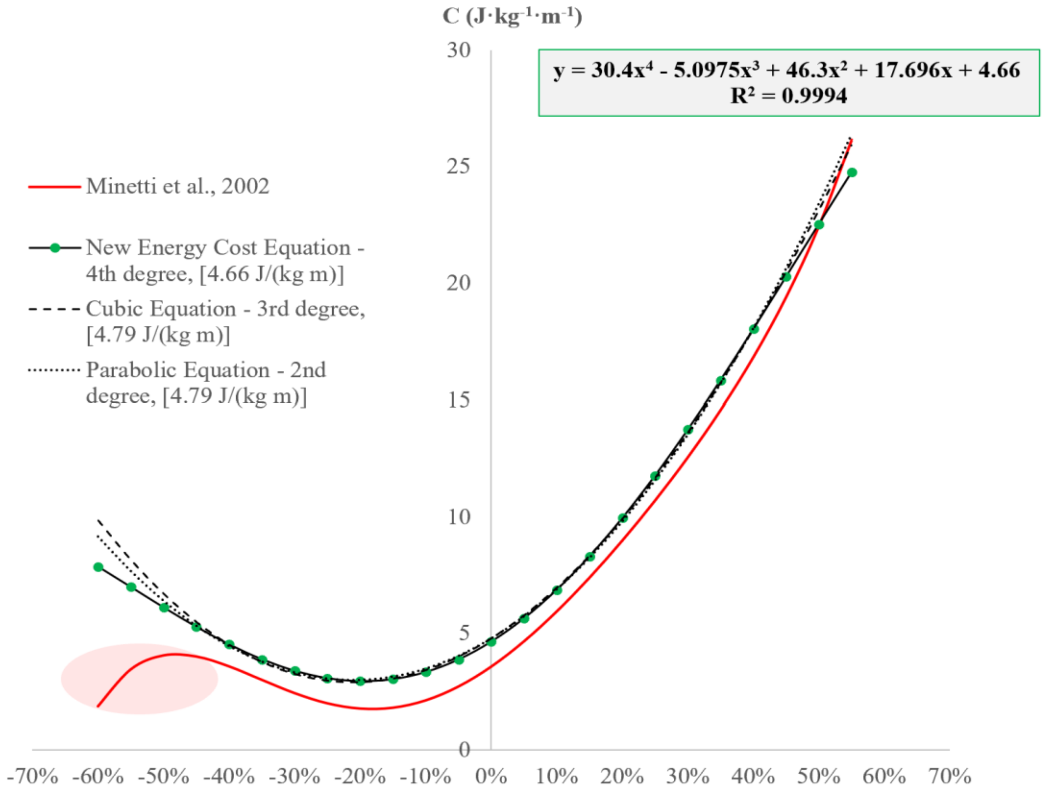


Figure 4.1. New energy cost paradigm (4^{th} order polynomial fit) relating to the C of running over grass in elite soccer as a function of the gradient with initial C_r constant at 0% equivalent to 4.66 $J{\cdot}kg^{-1}{\cdot}m^{-1}$. Where y = energy cost; x = gradient (%): $y = 30.4x^4 - 5.0975x^3 + 46.3x^2 + 17.696x + 4.66$ [new energy cost equation].

Maximal Oxygen Consumption ($\dot{V}O_{2max}$ mL·kg^{-1}·min^{-1})

The treadmill test started at 8 km·h^{-1} and increased in 2 km·h^{-1} increments every two minutes until 16 km·h^{-1} after which the gradient was elevated by 2.5% every 2-min until volitional exhaustion. The continuous $\dot{V}O_2$ and HR in each 5 seconds period was measured. $\dot{V}O_{2max}$ and HR_{max} were identified as the highest value of each at volitional exhaustion when an RER ≥ 1.15 and/or a whole [La-]b concentration ≥8.0 mmol·L^{-1} was reached (Edvardsen *et al.*, 2014). Immediately before and after the treadmill test, whole [La-]b concentration was measured from fingertip by portable lactate analyser (Lactate Pro ™ LT-1710; Arkray Inc., Kyoto, Japan).

Determination of C on grass: soccer specific high-intensity protocol

Field tests to determine C of running on UEFA standard grass surface were undertaken with soccer boots at the Artemio Franchi stadium (ACF Fiorentina, Florence, Italy). All participants were required to perform a soccer specific run for 8-min at varying speeds on a UEFA standard grass soccer field (Figure 4.2). Each subject was given a heart rate monitor (RS800sd, Polar Electro Oy, Kempele, Finland). Oxygen consumption ($\dot{V}O_2$) was determined on a breath-by-breath basis using a K4b^2 expired gas fraction analyser (Cosmed, Rome, Italy). The metabolic unit was calibrated using a 3-L syringe and a gas of known composition (16.00% O_2, 5.00% CO_2), respectively. During the steady state run, the K4b^2 analyser was placed in the harness around the shoulders of the participants. Before the start of the study, all subjects were familiarised with the equipment and the procedures. The data were recorded by the central unit located in the harness and sent telemetrically to a personal computer. $\dot{V}O_2$ data were averaged over 1-min. Blood lactate concentration [La-]b was determined using a portable lactate analyser (Lactate Pro ™ LT-1710; Arkray Inc., Kyoto, Japan) on a blood sample obtained from fingertip at upon completion of the test. Steady state oxygen uptake was defined as the mean of the last three minutes of the constant speed run.

Soccer-specific movement circuit

All participants were required to complete a combination of different running conditions on a UEFA standard grass pitch which was incorporated into a soccer-specific circuit based on previously collected data from a soccer database (Savoia *et al*., unpublished data; Figure 4.2):

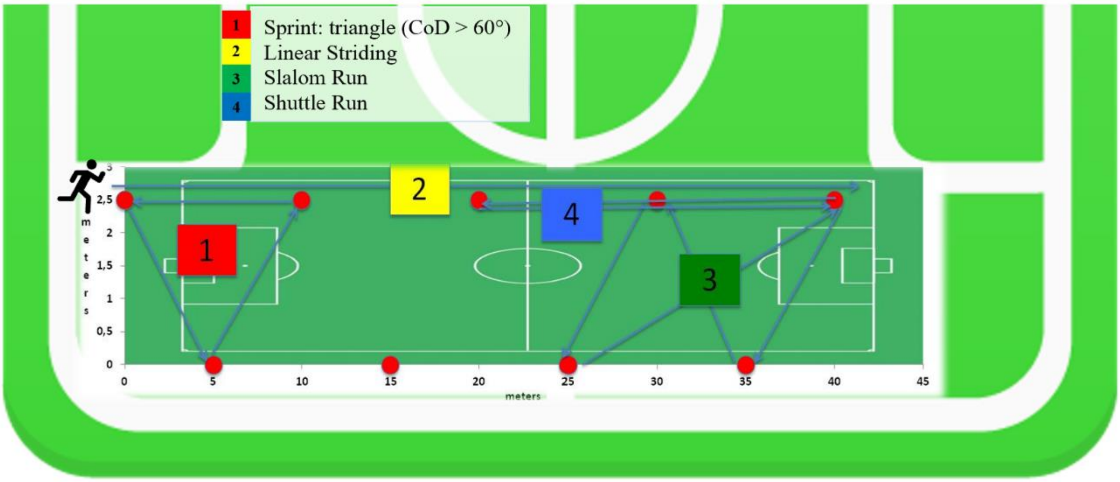


Figure 4.2. Displacement, direction and angle of change during non-linear soccer-specific circuit. Numeral relate to different activity tasks performed sequentially (see Table 4.1).

The soccer-specific protocol used in this validation study was based on data previously collected and stored in a soccer database (Savoia *et al*., unpublished data). Following further analysis of the data takes central features of soccer were taken into consideration in relation to specific patterns of movement; replicating its intermittent nature by introducing various actions, from maximal to the sub-maximal sprints, shuttles with changes of direction of varying angles. It includes slaloms around cones; including short passive pauses and longer recovery from the maximal sprints. The protocol was divided into 4 phases and repeated for 8 laps to give a total duration of activity of approximately eight minutes (Table 4.1). All activities commenced from a stationary start position and required participants to come to a complete stop at the end of the marked phase. A trundle wheel was used to measure the exact length of the soccer-specific circuit and each participant was familiarised with a sound dictation emitted at set times to regulate running speed. In addition, the angle of movement was measured and set at ± 60 degrees during the set-up. During the circuit, an iPod system (iPod nano, Apple, Cupertino, California) was used to emit the pacing beep every 5 seconds. As a spatial reference, multiple markers were positioned at fixed points depending on the running speed required.

Table 4.1. Soccer-specific protocol activities, distances, duration and recovery profiles. *Exercise intensity expressed as metabolic power ($W \cdot kg^{-1}$) is defined in brackets.

	Activity	**Distance (m)**	**Intensity ($km \cdot h^{-1}$)**	**Duration (s)**
1	Sprint: triangle (change of direction > 60°)	21.18	Max (> 26) *	~4-6”
2	Linear Striding	40	14.4 (23) *	~10”
3	Slalom Run	28.22	10.1 (20) *	~10”
4	Shuttle Run	20+20 (40)	14.4 (24) *	~10”

Calculation of energy cost (C) and metabolic power through gas analyser ($P_{\dot{V}O_2}$)

The energy costs of soccer-specific exercise (C) was determined 24 hrs after the last training bout and ~2-4 h after the last meal; it was evaluated during soccer-specific protocol performance. The energy cost of the soccer-specific activity protocol was calculated from the ratio of the total metabolic energy expenditure utilised above resting (E in joules) to the distance covered (*d* in meters). Energy cost above resting was calculated from the sum of the aerobic (Aer), anaerobic alactic (AnAl), and anaerobic lactic (AnL) energy expenditure. Briefly, energy expenditure derived from aerobic sources was obtained from the integral from the onset of exercise to the end of the soccer-specific protocol; the net $\dot{V}O_2$ values (averaged over 60-s), as obtained directly during the test minus the pre-exercise resting $\dot{V}O_2$ values (~3.5 $mL \cdot kg^{-1} \cdot min^{-1}$). Furthermore, the contribution from anaerobic alactic (AnAl) energy expenditure was determined by assessment of the $\dot{V}O_2$ uptake determined during the first 6 minutes of recovery upon completion of the protocol (fast replenishment). The net $\dot{V}O_2$ values obtained from the 4^{th} to 6^{th} minute of recovery were used to estimate the fast alactic O_2 debt, (AnAl) estimates. Finally, the lactic contribution to the overall energy expenditure (AnL) was estimated after exercise from the net blood lactate [La-]b accumulation above resting, by an energy equivalent of [La-]b accumulation in blood equating to ~3 mL·kg O_2 per mM (di Prampero, 1981; di Prampero and Ferretti 1999). The overall energy expenditure (EE = Aer + AnAl + AnL) for the duration of the test (8 minutes) was determined. This value of $\dot{V}O_2$ was multiplied by 20.9 based on the assumption that 1-mL O_2 yields 20.9 J, divided by the mass of the subject (kg) and distance covered (m) to generate an estimate of soccer-specific protocol C in $J{\cdot}kg^{-1}{\cdot}m^{-1}$. Data was converted to $W{\cdot}kg^{-1}$ using the formula:

$$\text{Metabolic Power } (W{\cdot}kg^{-1}) = C{\cdot}v$$

where C is energy cost and *v* are running velocity. Directly determined estimates were derived and compared with the C (and $W{\cdot}kg^{-1}$) calculated from the new energy cost equation.

Indirect calculation of metabolic power through GPS (P_{GPS})

Participants were tracked over the linear-sprints and the soccer-specific circuit using a GPS device (BT-Q1000eX 10-Hz, Qstarz, Taipei, Taiwan). Instantaneous velocity measurements were obtained for each trial. The GPS unit was placed on the upper back between the shoulder blades in a custom-made vest on all participants. According to Witte & Wilson (2004), the mean (± standard deviation) number of satellites 'used' during data collection was 9 ± 0.5 (satellites 'tracked': 11 ± 0.4). The mean HDOP during data collection was 1.0 ± 0.1. GPS velocity data (10-Hz) was sampled and synchronised at the first movement recorded above 0 $m{\cdot}s^{-1}$ to account for processing phase delays within the breath-by-breath output on the Cosmed $K4b^2$. Data were downloaded and analysed using (GPS Metabolic Power *LagalaColli* v9.076*d*, SPINItalia, Roma, Italy) to establish the time, speed, and distance; metabolic power, according to each player's individual body mass, was determined through the methodology of energy cost modelling as previously described and modified according to the new energy cost equation (Minetti *et al*., 2002; di Prampero *et al*., 2005).

Statistical analysis

All data were analysed using Statistical Package for the Social Sciences version 22 for Windows (SPSS, Chicago, IL, USA). All data were checked for normality using the Kolmogorov-Smirnov test. The validity of measurement of metabolic power between the new equation and the direct measurement was examined using a Wilcoxon test as data did not show normal distribution. Differences between methods were compared in accordance with the recommendations of Ludbrook (2010a) for the calibration of one method against another. The Pearson correlation coefficient was assessed to establish whether linear relationships between both methods were present. In accordance with Ludbrook's (2010a) recommendations, to gain estimates of fixed (intercept) and proportional (slope) bias the coefficients of the ordinary least products regression were determined via the LOSS function in SPSS version 25 (see Ludbrook [2012] for SPSS LOSS function commands). The SPSS LOSS function also provided the 95% CIs (via bootstrapping) for the intercept and slope along with the predicted and residual values for the raw data. The 95% prediction intervals were then calculated in the manner described by Altman *et al*. (2000). The results are presented as the mean ± the standard deviation throughout the text unless otherwise stated. Metabolic power estimates were represented by median ± IQR (interquartile range). The alpha level of significance was set at 5% (Kinear & Gray, 1995).

4.3: Results

Method comparison P_{GPS} and $P_{\dot{V}O2}$

Table 4.2 shows the estimates of fixed (intercept) and proportional (slope) bias for both P_{GPS} new and P_{GPS} (Minetti *et al.*, 2002). The Pearson correlation coefficient between P_{GPS} new and $P_{\dot{V}O2}$ (Cosmed K4b^2) was 0.66 (95% CI = 0.19 to 0.88) and for P_{GPS} and $P_{\dot{V}O2}$ was 0.63 (95% CI = 0.16 to 0.87). Along with the scatterplots, these *r* values were considered as being enough evidence for the presence of a linear association for both new methods with the $P_{\dot{V}O2}$ (gold standard). The scatterplots for P_{GPS} new on $P_{\dot{V}O2}$ and P_{GPS} on $P_{\dot{V}O2}$ showed no evidence of heteroscedasticity (Figure 4.3 and Figure 4.4). The new P_{GPS} model indicates that all variables are distributed around the line of unity indicating that it will both under and overestimate metabolic power relative to the P_{GPS} of Minetti *et al.* (2002), which routinely underestimates metabolic power across all ranges.

Table 4.2. Estimates of fixed and proportional bias from ordinary least products regression and their 95% CIs.

	Fixed Bias or Intercept	**Proportional Bias or Slope**
P_{GPS} new (Minetti *et al*., 2002 modified)	-0.803 (-8.393 – 6.788)	1.030 (0.531 – 1.528)
P_{GPS} (Minetti *et al*., 2002)	-1.591 (-9.358 – 6.177)	0.992 (0.482 – 1.502)

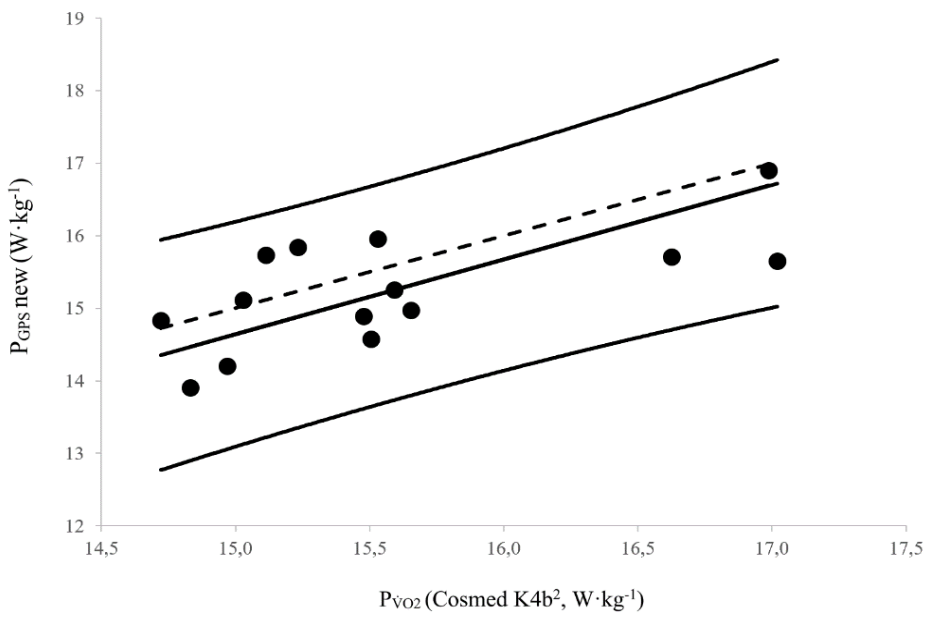


Figure 4.3. Ordinary least products regression of P_{GPS} new (Minetti *et al*., 2002 modified) values on $P_{\dot{V}O2}$ (Cosmed K4b^2) with the 95% prediction intervals.

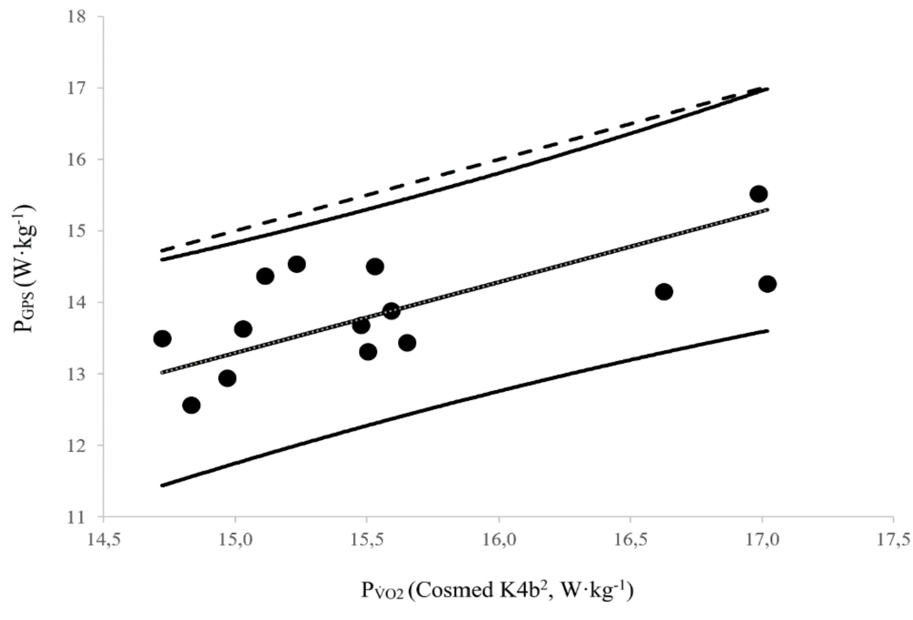


Figure 4.4. Ordinary least products regression of P_{GPS} (Minetti *et al*., 2002) values on $P_{\dot{V}O2}$ (Cosmed K4b^2) with the 95% prediction intervals.

Physiological response, locomotor and metabolic demands of the soccer-specific circuit.

The mean ± SD for $\dot{V}O_{2max}$ and HR_{max} values attained during the laboratory treadmill tests were 61.1 ± 4.3 $mL \cdot kg^{-1} \cdot min^{-1}$ and 194.2 ± 6.1 $b \cdot min^{-1}$, respectively. Mean ± SD $\dot{V}O_2$ and HR_{max} values elicited during the soccer-specific circuit performance were ~44.5 ± 2.3 $mL \cdot kg^{-1} \cdot min^{-1}$ (~73% $\dot{V}O_{2max}$), and 182 ± 8 $b \cdot min^{-1}$ (~94% of HR_{max}). Mean ± SD [La-]b values were 7.2 ± 1.6 $mmol \cdot L^{-1}$ post soccer-specific protocol performance, with a net increase of 6.2 ± 1.6 $mmol \cdot L^{-1}$ compared to resting values (Table 4.3).

Table 4.3. Physiological and metabolic responses to soccer-specific circuit ($K4b^2$ gas analysis). N = 13 players x 8 laps (8-min). *Treadmill incremental exercise test to $\dot{V}O_{2max}$.

Bioenergetic variables	Mean ± SD
$\dot{V}O_{2max}$ ($mL \cdot kg^{-1} \cdot min^{-1}$) *	61.1 ± 4.3
Rest $\dot{V}O_2$ ($mL \cdot min^{-1}$)	268 ± 21.6
HR_{max} last 2-min (%)	94.0 ± 2.0
[La-]b ($mmol \cdot L^{-1}$)	7.2 ± 1.6
$\dot{V}O_2$ exercise (O_2 debt included) [$L \cdot min^{-1}$]	3.4 ± 0.4
$\dot{V}O_2$ exercise (O_2 debt included) [$mL \cdot kg \cdot min^{-1}$]	44.5 ± 2.3
Energy cost ($J \cdot kg^{-1} \cdot m^{-1}$)	6.41 ± 0.31
$P_{\dot{V}O2}$ ($W \cdot kg^{-1}$)	15.6 ± 0.8

For illustrative purposes, only the soccer-specific circuit data, relative to 60-s or one complete lap, with exclusion of the other three laps, is displayed to highlight the raise in $\dot{V}O_2$ present and show the four locomotor activity phases (Table 4.1). To obtain the $\dot{V}O_2$

data related to body weight, the mL·min^{-1} for the kg of each subject were divided accordingly (Figure 4.5).

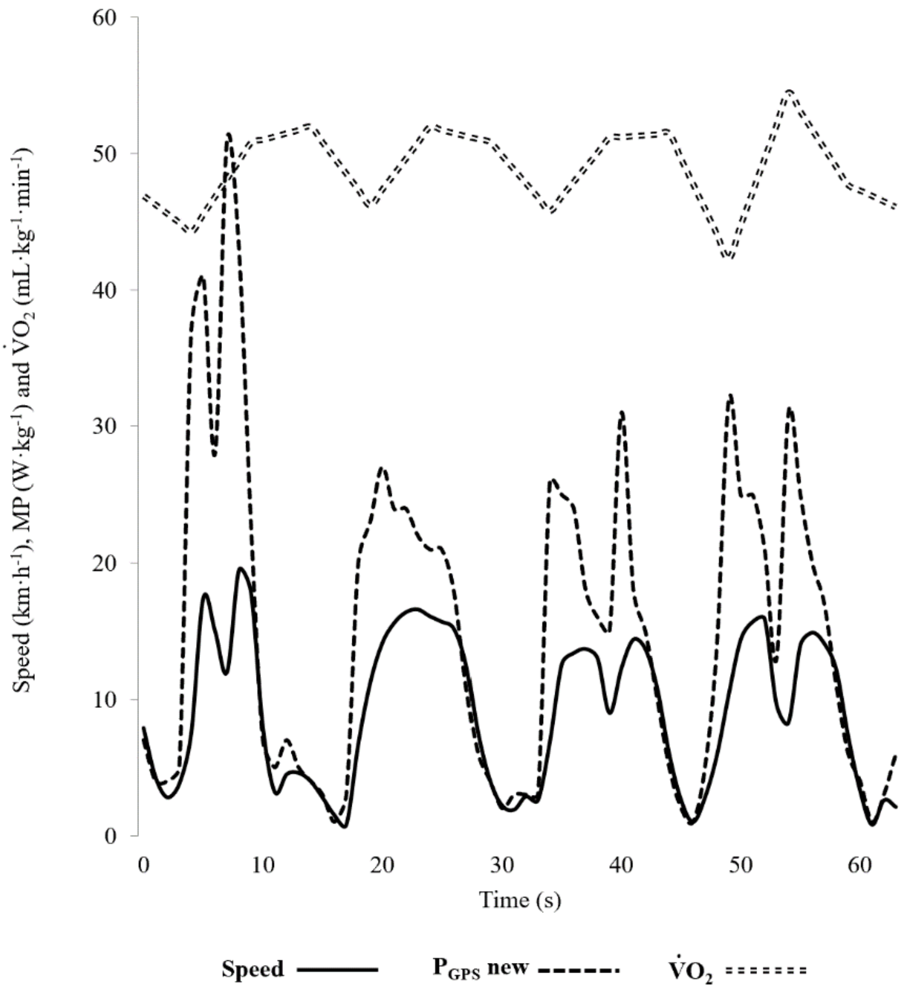


Figure 4.5. Oxygen uptake ($\dot{V}O_2$), speed and metabolic power estimated from locomotor demands (P_{GPS} new) during one lap (1-min) of the soccer-specific circuit in one of the representative players.

The results of the locomotor response of the players during the soccer-specific circuit can be found in Table 4.4. The other seven parameters evaluated in relation to the external load are displayed in Table 4.5.

Table 4.4. Time (s) and Distance (m) during the entire soccer-specific circuit in each speed and power categories (10-Hz GPS). N = 13 players x 8 laps (8-min). Data are mean ± SD.

Speed (v) and Power Categories	D (m)	T (s)
$v > 6$ km·h^{-1}	1060 ± 42	286 ± 11
$v > 11$ km·h^{-1}	902 ± 65	220 ± 10
$v > 16$ km·h^{-1}	277 ± 143	57 ± 29
$v > 20$ km·h^{-1}	12 ± 14	2 ± 2
P_{GPS} 0-10 W·kg^{-1}	171 ± 35	210 ± 9
P_{GPS} 10-20 W·kg^{-1}	469 ± 33	123 ± 15
$P_{GPS} > 20$ W·kg^{-1}	531 ± 71	143 ± 13
P_{GPS} 20-35 W·kg^{-1}	373 ± 52	97 ± 11
$P_{GPS} > 55$ W·kg^{-1}	37 ± 12	11 ± 4

Table 4.5. Locomotor and metabolic demands of the soccer-specific circuit (10-Hz GPS). N = 13 players x 8 laps (8-min). *v*, speed; MAV, maximal aerobic velocity; CoD, change of direction.

External Load	Mean ± SD
Total distance (m)	1168 ± 53
P_{GPS} (W·kg^{-1})	15.3 ± 0.8
High Acceleration > 50% a_{max} (% time)	21 ± 3
High Deceleration < -2 m·s^{-2} (% time)	17 ± 3
v > MAV (% time/total time)	12 ± 6
Bouts·min^{-1} > 20 W·kg^{-1} (n=)	4.7 ± 0.7
CoD > 30°·min^{-1} (n=)	21 ± 2

Metabolic Power: P_{GPS} vs $P_{\dot{V}O2}$

The metabolic power of the soccer-specific circuit was estimated through two energy cost equations (Minetti *et al*., 2002; Minetti *et al*., 2002 modified), and through direct measurement during the soccer-specific protocol in 13 elite players. Figure 4.6 illustrates the MP determined from GPS ($W \cdot kg^{-1}$) using all equations. There was no significant difference ($P > 0.05$) in the median MP derived from the new C equation by GPS during the soccer-specific protocol (15.3 ± 0.8 $W \cdot kg^{-1}$, IQR = 1.08 $W \cdot kg^{-1}$) which was found to be 2.2% lower than the median MP estimated by direct measurement with Cosmed $K4b^2$ (15.6 ± 0.8 $W \cdot kg^{-1}$, IQR = 1.14 $W \cdot kg^{-1}$). The prediction interval range from GPS displacement data expressed a lower prediction interval 13.7 ± 0.7 $W \cdot kg^{-1}$ relative to upper prediction interval 16.8 ± 0.8 $W \cdot kg^{-1}$. In general, under predicting metabolic power across all tasks. P_{GPS} using the original Minetti *et al*., (2002) equation shows mean ± SD values of 13.9 ± 0.8 $W \cdot kg^{-1}$ (IQR = 1.06 $W \cdot kg^{-1}$), which are found to be lower than the average $P_{\dot{V}O2}$ values established. The prediction interval range from GPS displacement data expressed a lower prediction interval 12.3 ± 0.71 $W \cdot kg^{-1}$ relative to upper prediction interval 15.4 ± 0.80 $W \cdot kg^{-1}$. In general, underpredicting metabolic power across all tasks demonstrating a high fixed bias. It should be noted that while the slopes of both equation lines are very close, large confidence intervals are expressed across both models. Metabolic power determined by GPS (P_{GPS} new) correlated highly with MP from direct measurement with the Cosmed $K4b^2$ ($r = 0.66$, $P < 0.05$).

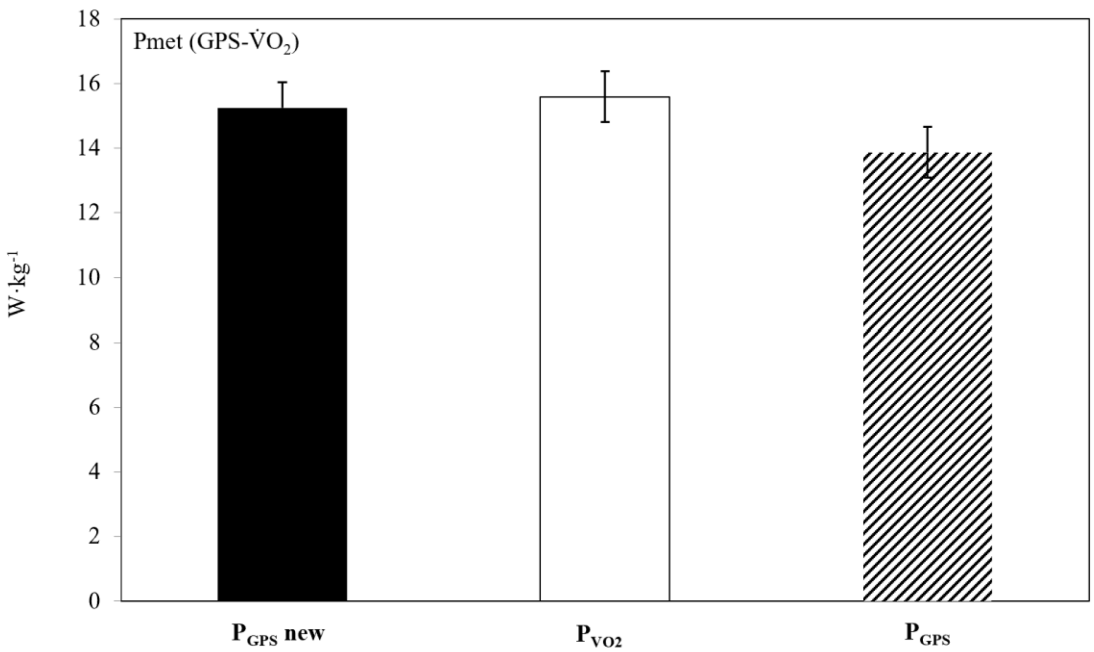


Figure 4.6. Metabolic power (W·kg^{-1}) derived from direct measurement by Cosmed K4b^2 ($P_{\dot{V}O2}$) and indirect assessment using two energy cost equations: P_{GPS} new (see Method section for further details) and P_{GPS} (Minetti *et al.*, 2002). Data are presented as median ± IQR.

Figure 4.7 compares the trend of $P_{\dot{V}O2}$ and P_{GPS} new during the 8 laps of soccer-specific circuit. Unlike the study performed by Buchheit *et al.* (2015a), it was not possible to separate metabolic power during the recovery phases within the soccer-specific circuit as these occurred intermittently within each minute (lap), and not at the end of each lap. In addition, the duration of recovery periods was shorter and more frequent, compared to recoveries of longer duration as was the case in their study. This is therefore detectable with independent histograms only (see Table 4.1). Only the bars relating to the integral minutes of work are shown, including the short passive recovery. $P_{\dot{V}O2}$ respects the physiology of physical exercise (di Prampero *et al.*, 1981) by adding in the calculation of the estimated energy expenditure (EEE), the energy obtained from the O_2 debt (anaerobic alactic [AnAl] and lactic [AnL] system).

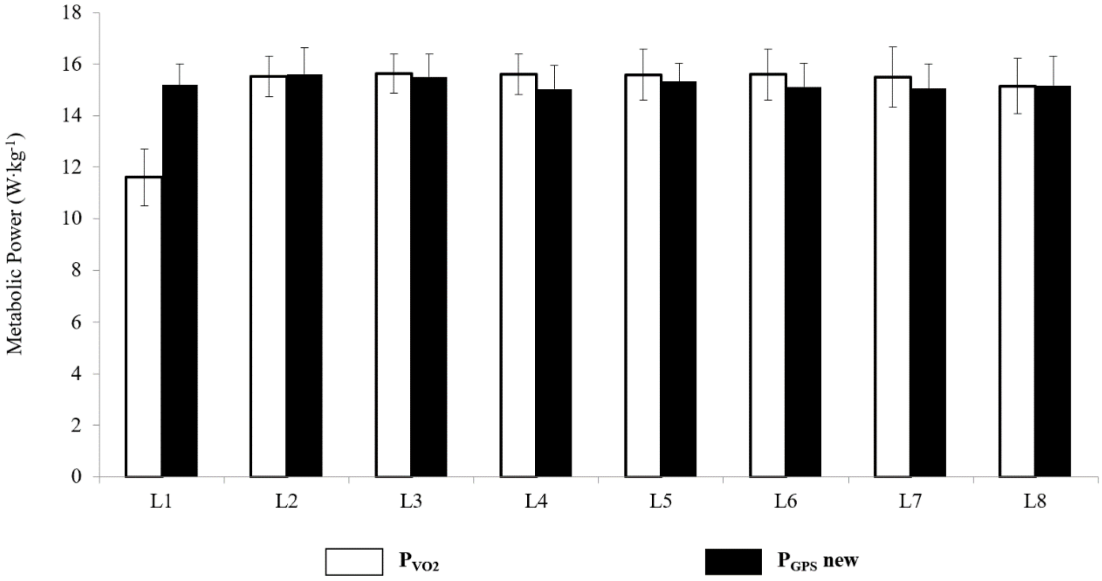


Figure 4.7. Average estimated metabolic power (expressed as W·kg^{-1}, mean ± SD) using either traditional calorimetry with oxygen uptake ($\dot{P}_{VO2}$, white bars) or locomotor-related metabolic power (P_{GPS} new, black bars) during the 8 laps of soccer-specific circuits (L1÷L8) with recovery included.

4.4: Discussion

The main finding of the study was that a new energy cost equation was determined which introduced a new constant term of 4.66 $J \cdot kg^{-1} \cdot min^{-1}$ and a regression prediction equation for the assessment of the C of running on grass in elite soccer players. This was established by investigating the average MP on a soccer-specific test through direct and indirect measurements of oxygen consumption using di Prampero's *et al*. (2005) approach while modifying Minetti's *et al*. (2002) equation of energy cost. As previously described in the introduction (section 4.1), the validation which takes into consideration locomotor kinematic data for the P_{GPS} calculation, must be applied to a context which is as soccer specific as possible. The method developed progressively through the intuitions of di Prampero *et al*. (2005) and Osgnach *et al*. (2010), together with the calculation of the energy cost (Minetti *et al*., 2002), cannot be applied to all sports, but only to those with a 'prevalently horizontal' mode, where the running on flat terrain represents the largest portion of the energetic performance model.

Stevens *et al*. (2015) described that it is currently not clear to what extent it is possible to compare metabolic power and energy cost between varying running activities. Therefore, validation of the different running activities is the goal of this research. There are some criticisms and limitations present within the current research studies available in the literature because of the protocols proposed and utilised. Present findings established that shuttle running using low speeds only, negating maximal actions, negatively affects the P_{GPS}; the underestimation observed is lower than the values found in other studies (e.g. Buchheit *et al*., 2015a), due to the reduction in error using 10-Hz sampling frequencies thus preventing a drastic decrease. Further, that type of running is not ideal for amateur soccer players; the proposed speeds will have minor influence and cost when establishing values of P_{GPS} (due to the absence of sub-maximal bouts) and is very much in direct relation with direct expenditure ($P_{\dot{V}O2}$), therefore amplifying the difference between the indirect measure and gold standard (Stevens *et al*., 2015).

Highton *et al*. (2016), observed that during a rugby-specific protocol incorporating contacts (collisions) and extensive passive rest (standing recovery) these were directly responsible for the underestimation of the EE estimated from the GPS data. The lack of coincidence between direct and estimated values were deemed to be a result of the inability of GPS to detect energy expenditure associated with non-locomotor exertion. Brown *et al*. (2016), examined the validity of a global positioning system (GPS) tracking system to estimate EE during exercise and field-sport locomotor movements in healthy adults. The findings related this study are difficult to be compared to our findings as the energy costs observed are for a different population sample. In addition, a GPS system that interpolates (via accelerometers) 5-Hz data, is deemed insufficient for the speed variations present in a soccer game and cannot be related to our results. Finally, the absence of blood lactate measurements is another limitation, and most importantly, the extensive recoveries incorporated in their exercises and then used for the calculation of EEE, result in an increase in the differences between $P_{\dot{V}O2}$ and P_{GPS}, and ultimately underestimating the latter.

Buchheit *et al*. (2015a), used a test incorporating a ball within their protocol, increasing the specificity related to soccer. However, they do so without considering the proportion of time a player continuously has the ball during a game, therefore making this a key factor as one of the causes of the P_{GPS} underestimation. Findings show that soccer players are in possession of the ball for less than 1% of the total time, and less than 2% compared to the total distance travelled during a match (Carling, 2010; Di Salvo *et al*., 2007). The energy cost of running with the ball is higher than without the ball, meaning the $\dot{V}O_2$ will rise during the technical parts and other activities with the ball (Buchheit *et al*., 2015a). Therefore, the P_{GPS} will always be underestimated since the kinematic data will be for most of the exercise and not significant in terms of high speed, acceleration and deceleration movement patterns. Potentially, the decelerations will be further emphasized (e.g. stop and kick, ball control during a slalom, passing and reception with a rebound wall *etc*.) which from a metabolic point of view (P_{GPS}) has a low energy cost. Additional limits are present as a 4-Hz GPS sampling frequency was used, the intensity percentage of the $\dot{V}O_{2max}$ was found to be up to 64% despite the "low" mechanical demands, and there was an absence of high speed (> 14.4 $km \cdot h^{-1}$) movement patterns as has already previously been observed in detail by Osgnach *et al*. (2016).

Considering previous research, it is important to consider previous limitations observed and create/develop a test that can validate P_{GPS} in soccer and be compared to a direct measurement ($P_{\dot{V}O2}$). It has been found that the three fundamental macro-aspects required to ensure that the energy estimation method proposed by di Prampero *et al*. (2005) and Osgnach *et al*. (2010) best represents the soccer game are: i) using a GPS system with a minimum sampling frequency of 10-Hz and a mathematical reduction (or smoothing, e.g. moving mean) of the speed data at 5-Hz to reduce noise in GPS elevation data, which has been found to be a methodologically verifiable value from a study performed by Gaudino *et al*. (2013), through performing calculations on contact and flight times in players on natural grass; ii) using an appropriate method to calculate the metabolic power in an intermittent submaximal exercise, including the anaerobic amount (di Prampero, 1981; Buglione & di Prampero, 2013); iii) using an appropriate experimental design by ensuring the work protocol includes an adequate population (e.g. elite soccer players) and a specific terrain for the C (i.e., natural grass). Further, the performance model [e.g. work:rest ratio and different locomotor activities (e.g. sprint, walking, jogging, high speed, CoD *etc*.)] must be suitable as the duration of pauses/recoveries play a decisive role on the metabolic response.

Regarding creating a test, other precautions related to the relationship between total high speed (TS) and total high power (TP), found to be between 55% and 32% in favour of TP in a study Gaudino *et al*. (2013a; 2014a) and the dimension changes as we move from SSG (small-sided games) scenario to the whole field (105x68 m) must also be considered according to Castagna *et al*. (2017). Therefore, choosing a soccer-specific circuit with an average metabolic power greater than the 11-12 $W \cdot kg^{-1}$ game intensity (Castagna *et al*., 2017), is necessary to respect the methodological criterion of power-time relationship on intermittent exercises (Jones & Vanhatalo, 2017). Furthermore, the high intensity actions (> 20 $W \cdot kg^{-1}$) are found to be around 4.7 actions per minute (see Table 4.5), a value that is higher than previous findings where only 2 intense actions per minute have been described in studies that only considered speed thresholds (O'Donoghue, 2002; Reilly & Williams, 2013). In addition, O'Donoghue (2002) shows that the most frequent recoveries are < 30-s, and about 57% of those < 20-s. It is important to note resting periods are never are never cumulative (pause of 30-s consecutive), but fractionated in the game and therefore, they must also be incorporated in this way when establishing a specific test. Further, Bradley *et al*. (2013) showed that recovery time, defined as the time that elapsed between high-intensity running actions, is about 52 ± 18 s. For this reason, in our soccer-specific circuit a maximal action (triangle) is repeated every single lap (1-min). If you compare this to Buchheit *et al*. (2015a), where the passive recovery of 30-s entirely spent at the end of the work minute, our proposed model of the soccer-specific circuit respects the intermittent nature of soccer by dividing the ~25-s of total recovery fractioned into shorter breaks (< 10-s).

According to Buchheit & Simpson (2017), Varley *et al*. (2017) and Malone *et al*. (2017), acceleration is measured from GPS data often derived from doppler-shift velocity. The time interval over which acceleration is calculated can significantly alter the data with a wider interval resulting in a smoothing effect on the data. Typically, acceleration is calculated over 0.2-s or 0.3-s when using 10-Hz GPS, although the most appropriate interval will depend on the brand and model of the device (Malone *et al*., 2017; Cardinale & Varley, 2017). In our soccer-specific circuit we preferred to export raw data from commercial software and process it independently. The method used to calculate the high accelerations, using the kinematic data of official Serie A matches (Savoia *et al*., unpublished data) as a reference database, is based on the equation by Sonderegger *et al*. (2016) and modified accordingly:

a_{max} (max acceleration): -0.18 (-0.17 to -0.19) $\cdot$ v_{init} + 5.91 (5.80 to 6.02)

where a_{max} is expressed in $m \cdot s^{-2}$ and the v_{init} in $km \cdot h^{-1}$ (see Table 4.5).

The conceptual basis of the new metabolic power approach to soccer as initially described by Osgnach *et al.* (2010) was predicated upon a formula that was based on a population non-specific to soccer. In this experiment we report data which assesses the C_r of running on grass and a new version of the ‘energy cost equation’ (Minetti *et al*., 2002 modified) and apply it to soccer-specific high-intensity movement scenarios for the first time. The principal finding of this study which directly determined physiological demands concurrently with GPS derived modelling of the metabolic power; indicate that in an elite soccer population the GPS metabolic power paradigm is a valid means of determining work rate during activities. No significant differences in MP expressed as $W \cdot kg^{-1}$ were evident between direct and indirect methods. Specifically, data indicates that where there are periods of repeated accelerations and deceleration superimposed on an aerobic background metabolic power estimates did not differ significantly from directly calculated estimates (Figure 4.6). Interestingly, metabolic power during the first phase of the soccer-specific protocol was higher possibly due to the higher metabolic demand associated with the acceleration phase of running. It has previously been determined that a very low metabolic demand is associated with phases of deceleration phase during non-linear runs and that acceleration or re-acceleration phases display an increased requirement (Hader *et al.,* 2016).

Further, we show that with a high frequency GPS system sampling at 10-Hz movement patterns are subject to a rapid change of directions and that the energy cost paradigm still provides a representative metabolic formula which is better suited to elite soccer match play and training. The accuracy of the GPS is based upon higher sampling frequency and accuracy for both acceleration and deceleration. Present data is also indicative of the essentially aerobic nature of soccer-specific movement patterns. The protocol as applied in this study elicited a physiological strain approximating just over 70% of $\dot{V}O_{2max}$ and 90% of HR_{max} which is in line with that reported during match play (Reilly *et al*., 1997; Di Salvo *et al*., 2007). Such observations provide support for the validation model utilised in the present study to compare directly and indirectly measured metabolic power and reflect its specificity to soccer match play.

4.5: Conclusion

In the present study a new energy cost equation was determined which introduced a new constant term of 4.66 $J \cdot kg^{-1} \cdot min^{-1}$ and a regression prediction equation for the assessment of the C of running on grass in elite soccer players. Estimates of energy expenditure (EEE) using this new equation were derived and compared to metabolic power measured directly using portable indirect calorimetry (Cosmed $K4b^2$) during soccer-specific movement patterns. The new equation ($P_{GPS\ new}$) on average slightly underestimates in elite players their metabolic power. Considering the new GPS example if a player has a directly measured metabolic power 15.5 of $W \cdot kg^{-1}$ then the estimated value will be predicted as 15.2 $W \cdot kg^{-1}$ but the prediction range could be as low as 13.64 $W \cdot kg^{-1}$ or as high as 16.8 of $W \cdot kg^{-1}$ with a range of ± 1.57 $W \cdot kg^{-1}$. Conversely, the old equation will under predict metabolic power, however, both equations should be viewed in the context of the width of the confidence intervals expressed.

Link between Chapter 4 to Chapter 5:

Metabolic power, taken together with kinematic acceleration and deceleration data, are central factors to gaining an understanding in relation to the performance model associated with match analysis which does not take into consideration solely speed variables. Validation of a test that can reflect the intensity of metabolic power in a sport-specific scenario is the key to compare the indirect calculation with direct energetic measurement. All this can be applied to soccer databases that store physical data in the matches, expanding the analysis to technical-tactical interpretations.

Chapter 5: Metabolic power approach in soccer: a new longitudinal match-performance analysis with a tactical key

5.1: Introduction

The modern game of soccer requires increasingly high-intensity psychophysical performances (Gregson *et al.*, 2010). Physical performance is only one factor that plays a role in achieving success. Therefore, the focus over recent years has meant that sport scientists have moved from player management using a physiological approach to an integrated/systematic approach considering more complex and in-depth game issues, related to technical and tactical match-play (Bradley & Ade, 2018).

Previous research has used a soccer performance model to asses match play with a focus on variables related to volume, such as total distance (TDC) and average speed (v, $m \cdot min^{-1}$) as well as total energy expenditure (EE, kJ) spent over a 90-min match. Over time such an approach has resulted in a more in-depth analysis of running performance (Akenhead & Nassis, 2016). For example, there is a greater focus on high-intensity efforts to gain a better understanding of these short but very relevant match phases (Bourdon *et al.*, 2017). Even though these phases might look quantitatively negligible, they have been found to be the most demanding in terms of cost (C_r) and therefore have a relevant impact on the whole match energy expenditure and specific fatigue of a soccer player (Osgnach *et al.*, 2010).

Due to the intermittent nature of soccer, there is a high demand to develop an accurate analysis of the dynamics of play. These dynamics have been shown to frequently switch between very short (< 3 s) sprints and quick decelerations (Whitehead *et al.*, 2018). Repeated accelerations and decelerations are only occasionally found to be linear as the presence of frequent changes of direction functional for dribbling, getting away from your opponent, and all the tactic-related runs highly influence the observation of linear runs (Sarmento *et al.*, 2014). The need to change speeds on a regular basis means the required muscular effort during soccer is highly variable. Because of these aforementioned factors, analysing physical performance in soccer is complex as it is important to take into account specific variables and an overall view of how this is represented, in terms of metabolic demand, using a metabolic power ($W \cdot kg^{-1}$) variable (di Prampero *et al*., 2015).

Therefore, the modern analysis of game performance must focus on both the physical variables of the player and the match-related decisions made by the soccer manager/coach, which influences and plays a major role in the performance of the player. Position-specific performance model studies have shown some limitations over time. Studies must examine the different game formations in addition to the different player positions (e.g. goalkeeper, defenders, midfielders, and attackers). The choice of formation made by the manager or coach (e.g., 4-3-3 or 3-5-2) influences a players required tactical effort as a function of the pitch area they must manage (Bradley *et al.*, 2011; Carling, 2011). In addition, this will also influence the relationship within the same player (e.g., different game by a central defender with 4-3-3 compared with 3-5-2) as to what formation he adopts. These are factors which have previously not been considered although they play a massive role in soccer performance and the outcome of a game.

Therefore, the aim of this study is to investigate main volume and intensity of specific physical variables in soccer and its relation to different formations, to establish whether there is a more effective formation and/or a formation more that minimises the between-halves performance decrease. Furthermore, we want to study team behaviour over the course of a whole home season (19 matches) to find out which variables influence the outcome of the first half and final match results and look at the relation to wins, draws, and losses.

5.2: Methods

Participants

One hundred and eighty-seven Serie A professional soccer players with age (mean ± SD) 27.3 ± 3.5 yrs, height 181.6 ± 6.1 cm and body mass 77.2 ± 8.9 kg took part of this study. A total of twenty Italian Serie A teams were involved in the 2012/2013 season. All players had at least ten years of experience playing in the National championships from a junior age. The experimental procedures were approved by the local Human Ethics Committee of Liverpool John Moores University. The study complied with the Declaration of Helsinki.

Research Design

All assessments were carried out in-season from August 2012 until May 2013. Only the nineteen official home league matches, which included the home team and their opponent, were used for further video match analysis. A total of ten players for each team were considered for the analysis. The initial formations adopted by the managers at the start of each half were used for analysis and changes made within halves were excluded. Three players which were dismissed during one of the matches by the official match-day referee were excluded from the analysis. Away matches were also not included in the analysis as cameras utilised to assess data for these matches had not been validated by Prozone/Amisco and not all stadiums had the appropriate facilities to facilitate analysis.

Video Match Analysis

Matches were analysed using STATS SportVU ® (STATS LLC, Chicago (IL), U.S.A.) software. The system tracks at a rate of up to 25-Hz and has been validated by the Technical University of Munich (TUM), with raw data being provided via cartesian coordinates by K-Sport (primary data has been smoothed at 5-Hz) (Linke *et al*., 2018).

The STATS SportVU tracking system transports the data of performance by extracting and processing coordinates of players (X, Y) and the ball (X, Y, Z) through HD cameras as well as sophisticated software and statistical algorithms. These cameras are located at roof level and capture the players' movements during matches. Subsequently, the data is analysed using proprietary software to create a dataset on each player's physical and technical performance. The new equations related to metabolic power were factored in post-match with the raw data files and used for subsequent analysis. The % high deceleration values are based on speed thresholds related to the time spent over -2 $m \cdot s^{-2}$ of all-time spent decelerating.

Statistical analysis

All data were analysed using Statistical Package for the Social Sciences version 22 for Windows (SPSS, Chicago, IL, USA). All data were checked for normality using the Kolmogorov-Smirnov test. Differences between groups for distance covered (m), distance covered at a speed > 16 $km \cdot h^{-1}$, high decelerations (%), high accelerations (%) and metabolic power ($W \cdot kg^{-1}$) were evaluated using a *t*-test to compare first and second half: for all players and formation. Univariate ANOVA (Bonferroni post-hoc) was performed to compare each variable of win, lose and draw considering first and second half. The results are presented as the mean ± the standard deviation throughout the text unless otherwise stated. The alpha level of significance was set at 5% and values of '0.000' given by the statistics package are shown here as $P < 0.0005$ (Kinear & Gray, 1995).

5.3: Results

Halves

Performance variables showed a main effect for half in distance covered and metabolic power (Table 5.1). Players covered shorter distances of 5138.0 ± 543.8 m in the 2nd half compared to 5339.8 ± 543.2 m in the first half ($P < 0.0005$). Significant changes for metabolic power were also observed with higher values in the 1st half of 11.4 ± 1.3 $W \cdot kg^{-1}$ compared to 11.0 ± 1.3 $W \cdot kg^{-1}$ during the 2nd half ($P < 0.0005$; Figure 5.1). It was also established that formations of 3-4-3, 4-3-3, 4-5-1, were significantly lower in the 2nd half for distance covered and metabolic power ($P < 0.05$). Overall distance covered at speed over 16 $km \cdot h^{-1}$ was also significantly lower in the first half compared to the second half distances covered of 890.9 ± 291.7 m compared to 854.0 ± 279.4 m, (Figure 5.2) respectively ($P = 0.009$). There was no main effect for half in % high acceleration and deceleration ($P > 0.05$; Figure 5.3 and Figure 5.4). Table 5.1 displays all the variables related to the play mode for the first and second half.

Formations

Performance variables showed a main effect for formation in distance covered and metabolic power (Table 5.1). The % of high accelerations did show a significant difference for style of play revealing that a 4-5-1 produced significantly lower % of high accelerations compared to 4-4-2 and 4-3-3. Figures show the longitudinal analysis of the comparisons between distance covered, distance covered at speed over 16 $km \cdot h^{-1}$, % of high acceleration/deceleration and metabolic power related to the Win, Lose or Draw for the first and second half.

Table 5.1. A comparison of the different game formations in performance variables between first half and second half in Serie A professional soccer players. *Significant difference between 1st and 2nd half ($P < 0.05$).

Formation (Total players)	1st half: Total Distance (m)	1st half: Distance >16 $km \cdot h^{-1}$ (m)	1st half: High deceleration (%)	1st half: High acceleration (%)	1st half: Metabolic Power ($W \cdot kg^{-1}$)	2nd half: Total Distance (m)	2nd half: Distance >16 $km \cdot h^{-1}$ (m)	2nd half: High deceleration (%)	2nd half: High acceleration (%)	2nd half: Metabolic Power ($W \cdot kg^{-1}$)
All	5339.8 ± 543.2	890.9 ± 291.7	13.1 ± 2.5	8.2 ± 1.8	11.4 ± 1.3	5138.0 ± 543.8*	854.0 ± 279.4	13.0 ± 2.3	8.1 ± 1.8	11.0 ± 1.3*
3-4-3 (40)	5222.0 ± 547.5	847.0 ± 249.5	12.5 ± 2.4	7.9 ± 1.6	11.1 ± 1.3	4989.4 ± 550.1*	805.3 ± 220.9	12.8 ± 2.3	7.9 ± 1.8	10.7± 1.0*
3-5-2 (40)	5457.9 ± 550.9	919.7 ± 313.5	13.4 ± 2.7	7.9 ± 1.8	11.7 ± 1.4	5347.5 ± 548.7	941.1 ± 342.0	13.0 ± 2.3	7.7 ± 1.5	11.4 ± 1.4
4-3-3 (50)	5305.6 ± 580.1	927.5 ± 325.0	12.9 ± 2.3	8.8 ± 2.1	11.3 ± 1.3	5100.1 ± 546.6*	859.8 ± 288.8	12.9 ± 2.5	8.7 ± 2.3	10.9 ± 1.4*
4-4-2 (37)	5289.1 ± 496.8	912.5 ± 307.7	13.5 ± 3.1	8.8 ± 2.2	11.4 ± 1.3	5195.1 ± 532.1	879.2 ± 293.2	13.5 ± 2.1	8.7 ± 2.0	11.3 ± 1.1
4-5-1 (20)	5424.5 ± 540.9	848.0 ± 263.0	13.2 ± 2.2	7.3 ± 1.1	11.6 ± 1.3	5057.9 ± 541.5*	784.7 ± 252.3	12.8 ± 2.5	7.4 ± 1.3	10.8 ± 1.5*

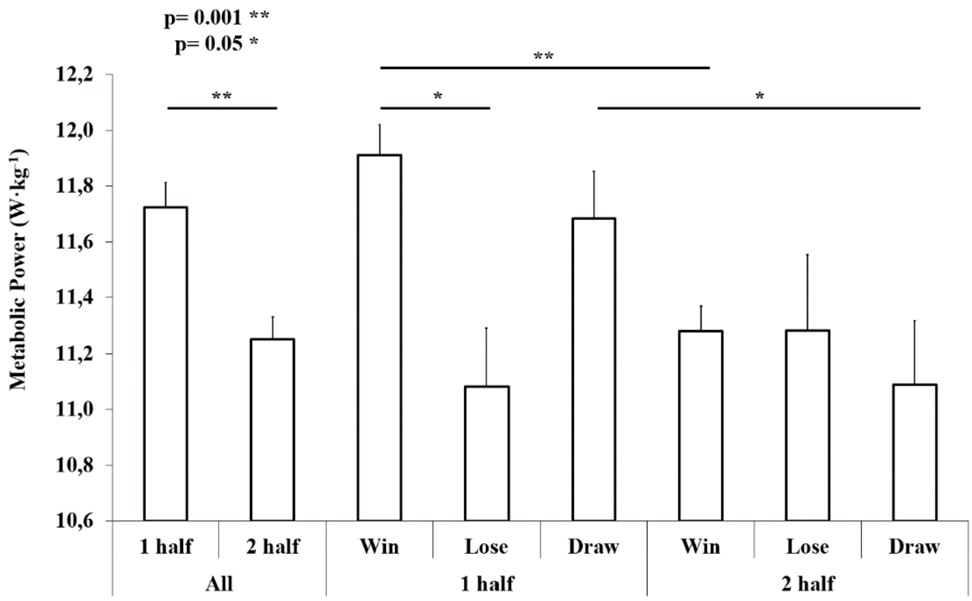


Figure 5.1. Metabolic power (W·kg^{-1}) by a Serie A team during different result conditions (W, L, D) comparing the first (0'-45') and the second half (45'-90').

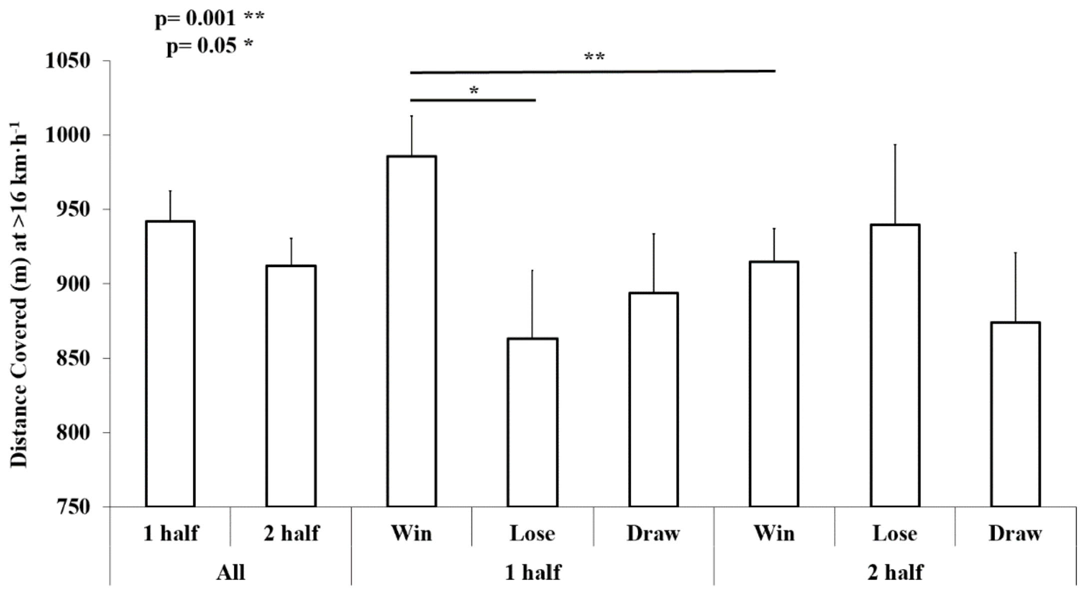


Figure 5.2. Distances covered over 16 km·h^{-1} by a Serie A team during different result conditions (W, L, D) comparing the first (0'-45') and the second half (45'-90').

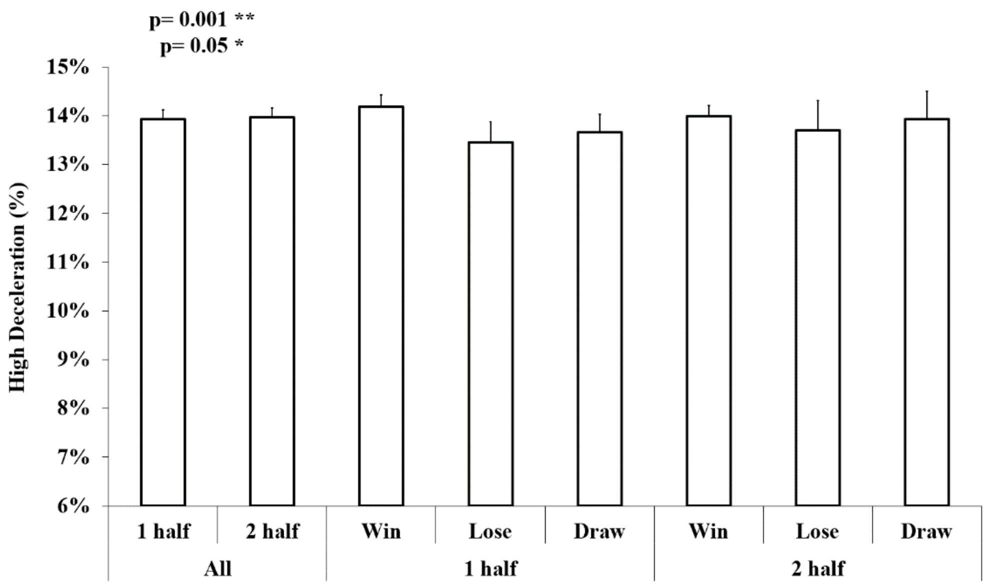


Figure 5.3. High deceleration (%) by a Serie A team during different result conditions (W, L, D) comparing the first (0'-45') and the second half (45'-90').

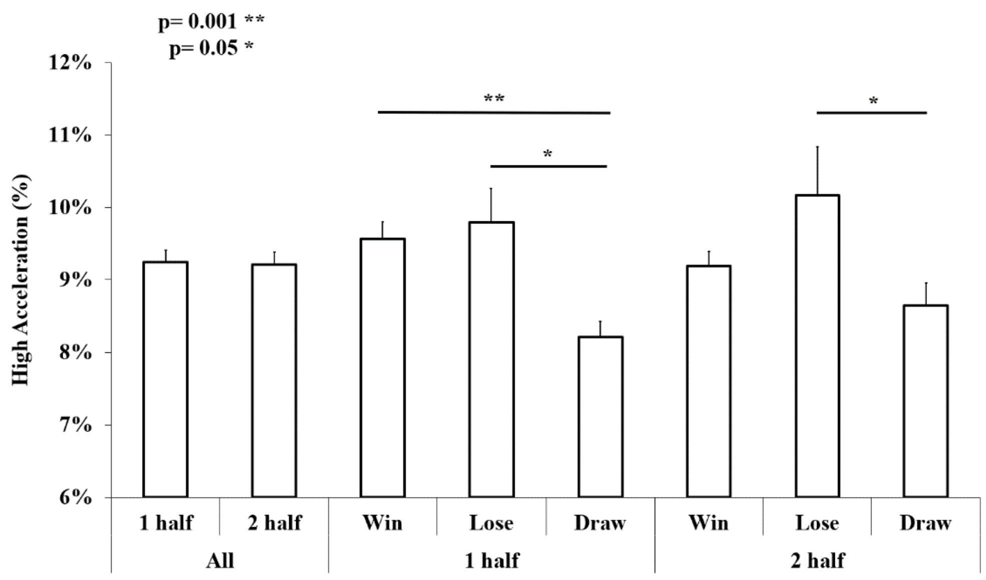


Figure 5.4. High acceleration (%) by a Serie A team during different result conditions (W, L, D) comparing the first (0'-45') and the second half (45'-90').

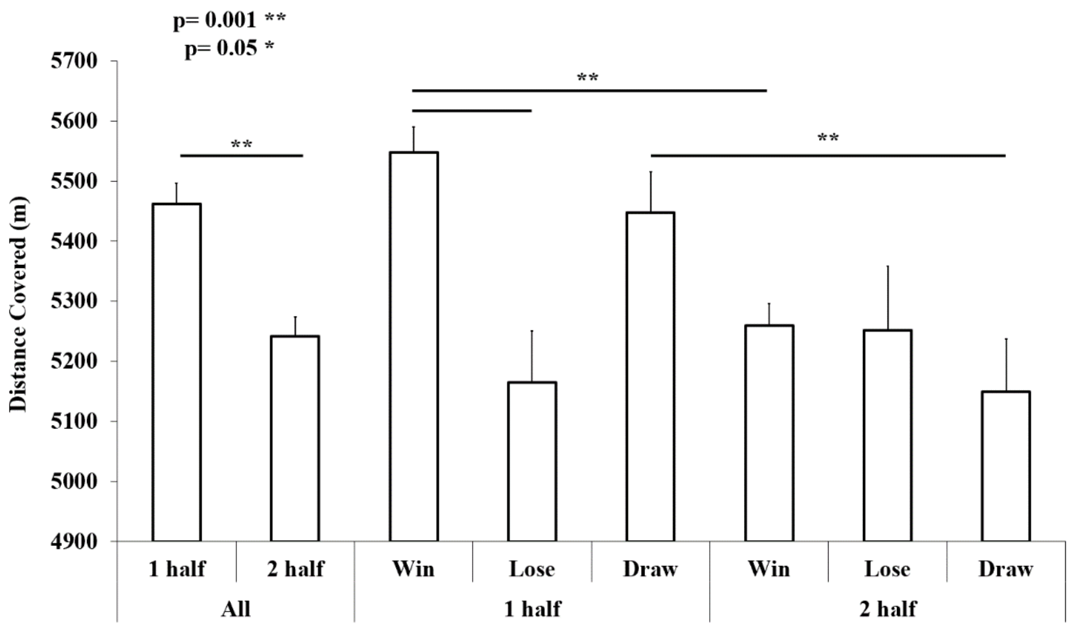


Figure 5.5. Average distance covered by a Serie A team (longitudinal analysis of 19 home matches) during different result conditions (W, L, D) comparing the first (0’-45’) and the second half (45’-90’).

5.4: Discussion

The aim of the study was to investigate main volume and intensity of specific physical variables in soccer and its relation to different formations, to establish whether there is a more effective formation and/or a formation more that minimises the between-halves performance decrease. Soccer teams will approach matches by using different formations depending on their opponent. They can vary by being more defensive, more attacking, or balanced in both. Therefore, the metabolic cost of a soccer player is not only influenced by their position on the pitch but also by the formation chosen by the manager together with the consequent technical-tactical movements undergone during a match. Soccer performance is influenced by several variables that display different levels of reliability and validity (Mackenzie & Cushion, 2013).

Our study showed a significant decrease in both physical performance (TDC) and metabolic power (MP) variables with almost all formations in the second half (Table 5.1). The mean MP data enables the data to be analysed and transferred into each player-specific metabolic profile by taking into account recovery during the game. The recoveries vary in action type and incorporate moments of standing still, walking or jogging and the intensity of actions affect the mean MP of each player. Therefore, TDC does affect mean MP, but other factors also need to be considered. In addition, without considering the first half or outcome of the match it is not possible to state that such decreases are due to only physiological fatigue. The slowing down of play is often a wanted metabolic energy-saving strategy operated by the team in control of the game, be it to maintain a draw or a win as the outcome. The tactics used (time wasting, “tactical” fouls, *etc.*) very often increase match inactive phases (together with an increase concomitant with referee whistles) and thus influence both physical performance and energy expenditure showing decreases that are clearly biased by the specific match situation (Carling, 2013; Lago-Peñas, 2012). Tactics evaluation is very relevant, because most successful teams showed a total, high-intensity, and very high-intensity running distances which was lower than the less successful teams. However, most of the successful teams showed better technical skills variables values (e.g. passes, percentage of successful short passes, crosses, *etc.*) than the less successful ones (Rampinini *et al*., 2009).

When analysing physical performance and metabolic expenditure variable decreases in second halves, it is interesting to highlight that 3-5-2 and 4-4-2 formations are not characterised by such changes and therefore they could be an energy-saving or performance-preserving formation (Table 5.1). When winning and drawing a significant decrease was found in the covered distances in the second half compared to previous studies was found (Rampinini *et al*., 2009). When winning, shorter distances higher than 16 $km\cdot h^{-1}$ were covered in the second half. However, while losing there was no significant differences in distances and distance covered by speeds higher than 16 $km\cdot h^{-1}$ in second half.

High ($< -2\ m\cdot s^{-2}$) decelerations (less energy-demanding) do not change significantly over halves or in relation to match outcome (Figure 5.3). However, the winning team performs more ($> 2\ m\cdot s^{-2}$) accelerations (a more energy-demanding behaviour) than teams which are drawing in the first half and in turn, teams which are drawing accelerate more than losing counterparts in both the first and second halves (Figure 5.4). More significant changes in speed over time take place during winning situations with the initiation of the acceleration playing a key role in the estimation of high acceleration actions (Sonderegger *et al.*, 2016). Limited to the longitudinally considered home team, losses come together with less accelerations. Metabolic power analysis report results like distances covered, demonstrate that winning teams have higher power compared to the losing teams in the first half and teams, whereas winning and drawing teams show power decreases during the second half (Figure 5.1). However, losing teams do not show significant power values in the second half.

5.5: Conclusion

In conclusion, it appears that future investigations on soccer should also focus on variables other than physical performance and metabolic cost. Tactics are influenced by many factors: historical data (previous results against opponent and others) and external factors (match location, competition, table-rank, referees, weather, *etc*.) in addition to individual and team tactics, physiological, and technical skills factors (Rein *et al*., 2016; Kyprianou & Farioli, 2018). Therefore, tactical investigations could effectively take advantage of big data and modern machine learning technologies, by collecting specific match data variables and transforming this through artificial intelligence, providing coaches and support staff with more in-depth insights into team-performance through the combination of physical and tactical data.

Link between Chapter 5 to Chapter 6:

The study of high intensity physical parameters in soccer is useful for describing performance. To improve the training methodology, match information must be compared with the daily scenario, by applying the calculations and observations to these training sessions. The quality of the exercises/drills with the ball must simulate the specific situations of the matches as much as possible. The only way to do this effectively is through the application of similar technological systems that monitor players.

Chapter 6: Training load analysis and physical match performance variables in elite soccer: is there any correlation?

6.1: Introduction

Soccer is a complex sport which garners great interest from the entire world. It is characterised by the unpredictable movement patterns during matches and training sessions (Wallace & Norton *et al*., 2014; Di Mascio *et al*., 2015). The most frequent movements during matches can be classified as short multi-directional high-intensity efforts in combination with more extended periods of low-intensity activity (Bangsbo *et al*., 2006). In the past, before any of the currently utilised physiological and mechanical measures were available, sport scientists aimed to solely evaluate the distance covered or the time spent at different running speeds (Castellano *et al*., 2014). With the increase in scientific and technical knowledge, it is now possible to measure advanced parameters such as the energy expenditure using continuous heart rate recordings along with metabolic power, and acceleration/deceleration patterns (Osgnach *et al*., 2010). To assess these traditional and advanced parameters, scientists and researchers have evaluated major competitions such as the Italian Serie A (Vigne *et al*., 2010; Mohr *et al*., 2003), German Bundesliga (Hoppe *et al*., 2015; Bradley *et al*., 2014; Di Salvo *et al*., 2010), Spanish La Liga (Castellano *et al*., 2011), English Premier League (Bradley *et al*., 2009; Di Salvo *et al*., 2009), French Ligue 1 (Carling & Dupont, 2011), UEFA Champions League and numerous international tournaments (da Mota *et al*., 2016; Schimpchen *et al*., 2016).

Over the last four decades, many researchers have turned their efforts to evaluate the physical and mechanical performance of soccer players. To do this, practitioners depend on some advanced tools called 'Sophisticated Systems' such as local position measurement (LPM) (Ogris *et al*., 2012), semi-automated computerized tracking systems (Di Salvo *et al*., 2006) and global positioning systems (GPS) (Carling *et al*., 2008; Lago-Ballesteros *et al*., 2012). All of these systems/technologies record, process and estimate the quick responses of the body and the substantial contributions of all players during the matches and/or training sessions (Harley *et al*., 2011). Moreover, they demonstrate a high ability to examine these findings with high accuracy (Ogris *et al*., 2012; Di Salvo *et al*., 2006; 2009). However, some of these systems/technologies show greater value than others. For example, the semi-automated computerized tracking system tends to report slight to moderate distances covered during high intensity while the GPS technology shows moderate to significant findings (Harley *et al*., 2011; Randers *et al*., 2010). Due to these differences, many researchers have conducted several studies to compare these systems/technologies.

Because of this technological revolution, it has provided practitioners with the opportunity to combine and compare aspects of physical performance parameters in match-play with the load proposed in training. This information has placed a high emphasis on coaches, performance analysts and exercise physiologists to utilise this model as a performance reference (Mackenzie & Cushion, 2013; Filetti *et al*., 2017). Over the last few years, the technical-tactical evolution in soccer, primarily based on the aspect of ball possession during matches, has resulted in training provision to focus on increasingly smaller playing fields (i.e., SSG). It is believed that this constrains players to find solutions in scenarios where less space and time are available for "passing", one of the major aspects of tactical nuclei within the dynamics of the game. Furthermore, using technical-tactical (technical efficiency index; TEI) and physical (physical efficiency index; PEI) indices provides means to gather a greater understanding of training and competition aspects related to match-play (Filetti *et al*., 2017).

The use of SSG is widely employed in soccer training to develop skills and to improve performance and has become a popular training method for all ages independent of skill level (Hill-Haas *et al*., 2011). Training drills incorporating SSG provide players with situations related to match-play instances and enable them to reproduce aspects linked with physical, physiological and technical demands of competitive soccer (Little, 2009). It is believed that training game play (e.g., SSG), which manipulates parameters of space and time, while adding and incorporating tactical constraints, remains one of the most important ways of training to help develop physical qualities in an intermittent and specific scenario for soccer players (Gaudino *et al*., 2013a; 2014).

The speed category approach has been found to only provide a partial figure of actual game physiological demands as it does not take into account aspects related to match acceleration and deceleration (Osgnach *et al*., 2010). Therefore, in recent years, kinematic values (e.g. acceleration, deceleration, speed *etc*.) are some of the most commonly used parameters in soccer. Metabolic power, which represents a synthetic index of the intensity containing both the active part of the work and the recovery period, has also been used to provide more information. The metabolic power approach constitutes of an integrated method potentially useful to track the game and training demands of players (Osgnach *et al*., 2010). According to Manzi *et al*. (2014) further studies should be carried out to further examine the metabolic power responsiveness to training in professional soccer.

Assessment of SSG performed by Dalen *et al*. (2019) found that high intensity running, and sprinting performance of official matches were not met by 4 *vs*. 4 nor 6 *vs*. 6 SSGs. However, they suggested that the use 4 *vs*. 4 games are a good method of training acceleration and player load tolerance. The ability of coaches to adjust training sessions according to the physical factors they wish to prioritize plays a vital role on the effectiveness of physical training the coach is focusing on. Other findings related to SSG found that as pitch size decreased (10 *vs*. 10 > 7 *vs*. 7 > 5 *vs*. 5), the total distance, distances run at high speed (>14.4 $km \cdot h^{-1}$) as well as absolute maximum velocity, maximum acceleration and maximum deceleration also decreased. However, the number of moderate accelerations and decelerations as well as the total number of changes in velocity were greater as the pitch dimensions decreased (5 *vs*. 5 > 7 *vs*. 7 > 10 *vs*. 10). Further detailed analysis of these drills is pivotal in contemporary soccer. It will enable provision of an in-depth understanding of the workload imposed on each player which consequently has practical implications for the prescription of the adequate type and amount of stimulus during exercise training (Gaudino *et al*., 2014). To our knowledge no studies have previously compared the number of accelerations made in SSG and friendly matches in a soccer context and this Chapter (study) will be the first to do so. It was established that the number of accelerations was higher during SSG used as part of training than it was during match-play (Castellano & Casamichana, 2013). This finding could be related to greater neuromuscular fatigue and increased metabolic cost during matches (Osgnach *et al*., 2010). Findings demonstrate that a 6-a-side SSG can replicate the high-intensity demands of 11-a-side full-sized pitch in youth soccer players when the area per player of the SSGs is approximately half of the full-sized pitch. However, although SSGs can replicate the high-intensity demands of 11-a-side, the speed approach underestimates the high-intensity demands of SSGs and 11-a-side compared with the metabolic power approach (Goto & King, 2019).

The main aims of all these studies is to improve the physical and mechanical performance of the players in addition to providing a clear vision of the what the most appropriate tactics are for the team to win the match and be successful. Tactics can be defined as "the action or strategy carefully planned to achieve a specific end", therefore, the selection of the appropriate tactic plays an essential role during every pre-game preparation phase, to ultimately win the game (Kannekens *et al*., 2011; Sampaio & Maçãs, 2012). Nevertheless, we observe that little progress has been made regarding optimising the array of metrics used by applied staff within clubs. Therefore, in this study, we aim to investigate the correlation between the parameters analysed during training sessions and during official matches of elite soccer, as well as investigating the 'functional model' proposed in training.

6.2: Methods

Participants

Eighteen highly trained male soccer players (4 central defenders, 4 wide defenders, 3 central midfielders, 3 box-to-box midfielders, 2 wingers and 2 strikers) from a professional team from Italy with age (mean ± SD) 26.7 ± 2.8 yrs, height 180.2 ± 5.1 cm and body mass 78.5 ± 7.9 kg took part in this study. Players were monitored during four months of full training (including pre-season and in-season) and over 26 matches (14 Serie A matches, 9 UEFA Europa League matches, and 3 friendly matches), which took place from July 2017 until November 2017. All players had at least ten years of experience playing in national championships from a junior age. Verbal explanation of the experimental procedure was provided; this included the aims of the study, the possible risks associated with participation and the experimental procedures to be utilised. The experimental procedures were approved by the local Human Ethics Committee of Liverpool John Moores University. The study complied with the Declaration of Helsinki.

Research Design

This is a prospective, single-centre study. All players underwent the same type of training session: game play with different sized pitches (40x20m to 105x68m) and number of players (5 to 10 a-side) at the same time periods. All demographic data was collected during the allocation stage; before the beginning of the training prescription. The physical and intensity parameters during the training sessions were evaluated using high-frequency GPS: STATS GPS ® K-Live at 50-Hz, [K-Sport Universal, Montelabbate (PU), Italy]. During the matches, the intensity parameters were evaluated using Video Match Analysis: STATS SportVU ® [STATS LLC, Chicago (IL), U.S.A.], tracking at rates of up to 25-Hz validated by Technical University of Munich (TUM), raw data were provided via cartesian coordinates by K-Sport (primary data has been smoothed at 5-Hz, see Chapter 4). The players analysed and used for subsequent analysis either ended the game or were substituted no more than 5 minutes from the final whistle (≥ 85-min of match-play).

GPS technology

A high-frequency STATS GPS ® K-Live at 50-Hz, [K-Sport Universal, Montelabbate (PU), Italy] was used to assess GPS. This technology allows the trainer to monitor the training performance of players and objectively make live decisions according to actual data. The system can calculate over 300 metrics in real-time. Data are always precisely transferred live during training and partially analysed post-session. To ensure precision of data analysis, the raw data file post-session is downloaded and subsequently analysed to reduce possible error. In addition, this technology enables us to follow the three-dimensional movement of an individual player or team to be tracked over time. Besides, it assesses different positional workloads, establishes training intensities, and monitors changes in the physiologic demands of the players. To achieve high signal quality and allow for satellite lock, we activated all GPS devices 15 minutes before data collection. The signal quality was evaluated through the number of connected satellites (11 ± 1.4) and the horizontal dilution of precision (0.9 ± 0.1) according to Witte and Wilson (2004).

Video Match Analysis

For video match analysis the STATS SportVU ® [STATS LLC, Chicago (IL), U.S.A.] was used which tracks at a rate of up to 25-Hz and is validated by Technical University of Munich (TUM), raw data were provided via cartesian coordinates by K-Sport (primary data has been smoothed at 5-Hz). K-Sport and STATS SportVU ® are linked and use the same technology through a joint-venture, increasing the reliability of the data collected. The STATS SportVU tracking system transports the data of performance by extracting and processing coordinates of players (X, Y) and the ball (X, Y, Z) through HD cameras as well as sophisticated software and statistical algorithms (Linke *et al*., 2018). Through cameras located at roof level, player movements were captured during matches and the data analysed by proprietary software to create a dataset on each player's physical and technical performance.

Measurement Outcomes

Primary Endpoint: To assess the correlation between the physical performance variables during training game play and the same parameters observed over the course of a full match. *Secondary Endpoints:* To assess the following physical performance parameters: average metabolic power (MP, $W \cdot kg^{-1}$), distance at high speed (> 16 $km \cdot h^{-1}$), distance at high acceleration (> 2 $m \cdot s^{-2}$), distance at high deceleration (< -2 $m \cdot s^{-2}$) and distance at high metabolic power (> 20 $W \cdot kg^{-1}$) in comparison to the functional model of the same between training and matches.

Statistical Analysis

All data were analysed using Statistical Package for the Social Sciences version 22 for Windows (SPSS, Chicago, IL, USA). For correlation the method of Bland and Altman (1986; 1995) was used, which takes into account multiple values being obtained from each participant. The Bland and Altman plot method (95% limits of agreement) was used to compare all physiological and kinematic variables (metabolic power, distance at high metabolic power, high acceleration and high speed) between official match and training game play (measurement agreement). Linearity was assumed after visual inspection of variable-associated scatter plots. Variables association was assessed using Pearson's product moment correlation coefficients (i.e., *r*) and provided with the corresponding confidence interval at 95%. The magnitude of correlation was classified as trivial (≤ 0.2), small (> 0.2–0.6), moderate (> 0.6–1.2), large (> 1.2–2.0) and very large (> 2.0) based on guidelines from Hopkins (2002) and Batterham & Hopkins (2006). The results are presented as the mean ± the standard deviation throughout the text unless otherwise stated. Also, 95% confidence intervals (CIs) are presented where appropriate. The alpha level of significance was set at 5% (Kinear & Gray, 1995).

6.3: Results

There was a significant difference in distance at HI speed (>16 $km \cdot h^{-1}$) with values 38.9% in official matches compared to training game play ($P = 0.0011$, CI = 0.36 to 0.88). Distance at HI acceleration (> 2 $m \cdot s^{-2}$) were also found to be significantly different between official matches and training game play ($P = 0.0013$, CI = 0.34 to 0.88) with lower distances of 12.4% during official matches. Results for distance at HI MP (> 20 $W \cdot kg^{-1}$) also found significant differences between official matches and training game play ($P = 0.0001$, CI = 0.64 to 0.94) with observed values 17.7% higher during match play. Measures of metabolic power also found significant differences between official matches and game play ($P = 0.0001$, CI = 0.54 to 0.92) with values 7.5% higher during official match play. Only distance at HI deceleration (< -2 $m \cdot s^{-2}$) found no differences between game play and official matches.

Bland Altman plots for all physical performance variables can be found in Figure 6.1. All variables showed a positive correlation ranging from $r = 0.71$ to $r = 0.85$ (see Table 6.1) except for distance at HI deceleration (< -2 $m \cdot s^{-2}$) which showed a negative correlation ($r = -0.21$). Scatter plot of the resulting relationship between distance covered at high speed (> 16 $km \cdot h^{-1}$) among official match and training game play can be found in Figure 6.2.

Table 6.1. Person correlation (*r*), its magnitude (*d*) and 95% confidence interval (LoA) between the same physical performance variables among Game play and Official match. Statistical significance is shown as P values.

Game play *vs* Official match	Pearson correlation coefficient	Magnitude of correlation	Mean bias	Limits of agreement		P (H_0: Mean=0)
				Lower	Upper	
Average speed ($m \cdot min^{-1}$)	0.83	*Very large*	-11.41	-21.48	-1.36	<0.0001
95% CI	0.59 to 0.93		-13.97 to -8.86	-25.92 to -17.03	-5.80 to 3.08	
Metabolic Power ($W \cdot kg^{-1}$)	0.79	*Very large*	-8.03	-18.49	2.42	<0.0001
95% CI	0.53 to 0.92		-10.69 to -5.38	-23.11 to -13.87	-2.19 to 7.04	
Speed $m \cdot min^{-1}$ > 20 $W \cdot kg^{-1}$	0.85	*Very large*	-19.65	-38.19	-1.11	<0.0001
95% CI	0.63 to 0.94		-24.35 to -14.95	-46.39 to -30.00	-9.30 to 7.08	
Speed $m \cdot min^{-1}$ > 16 $km \cdot h^{-1}$	0.71	*Large*	-47.79	-73.92	-21.66	<0.0001
95% CI	0.35 to 0.88		-54.42 to -41.16	-85.47 to -62.38	-33.21 to -10.11	
Speed max ($m \cdot s^{-1}$)	0.34	*Moderate*	-26.45	-35.49	-17.42	<0.0001
95% CI	-0.26 to 0.63		-28.75 to -24.16	-39.48 to -31.50	-21.41 to -13.03	
% Equivalent distance	0.65	*Large*	19.64	3.05	36.24	<0.0001
95% CI	0.26 to 0.85		15.43 to 23.85	-4.28 to 10.38	28.90 to 43.57	
Speed $m \cdot min^{-1}$ > 2 $m \cdot s^{-2}$	0.69	*Large*	-11.74	-7.51	31.00	0.0001
95% CI	0.33 to 0.87		-6.85 to 16.62	-16.02 to -0.99	-22.49 to 39.51	
Speed $m \cdot min^{-1}$ > -2 $m \cdot s^{-2}$	-0.21	*Small*	13.39	-25.44	52.23	0.0107
95% CI	-0.61 to 0.28		3.54 to 23.25	-42.61 to -8.28	35.07 to 69.40	

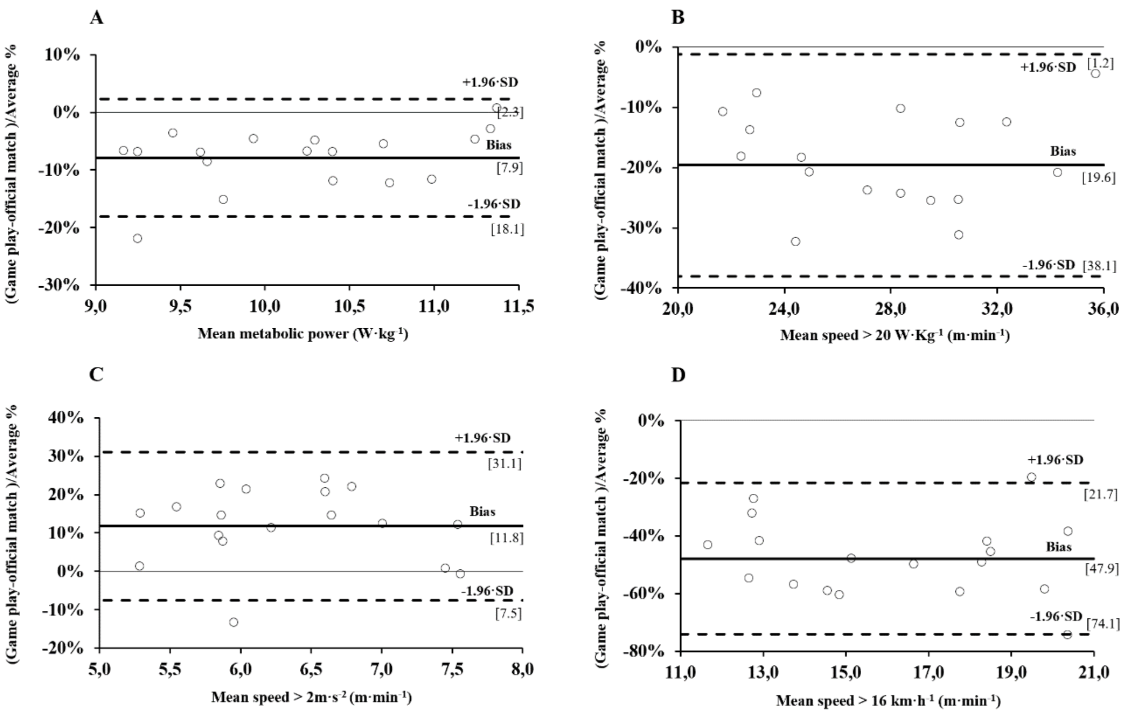


Figure 6.1. Bland-Altman plots for all physical performance variables studied. The solid lines correspond to the mean differences as % (d) between the Official match and Training game play for Metabolic Power (**A**), HI MP (**B**), HI acceleration (**C**) and speed (**D**); the upper and lower dashed lines represent the 95% LoA (limits of agreement).

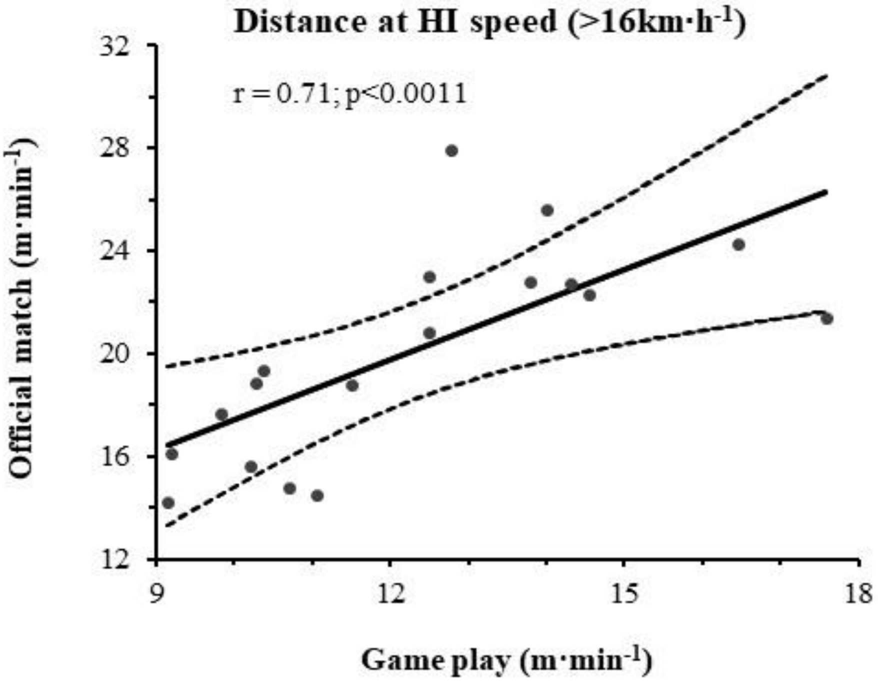


Figure 6.2. Scatter plot of the resulting relationship between distance covered at high speed (> 16 km·h^{-1}) among Official match and Training game play; r = 0.71 (95% confidence interval, 0.35–0.88); P < 0.01.

6.4: Discussion

The aim of the study was to investigate the correlation between the essential parameters related to high intensity actions and metabolic power analysed during training game play and official match play of elite soccer, as well as investigating the ‘functional model’ proposed in training. Table 6.1 shows the existence of positive correlations between the performance data analysed during the games played in training and locomotor data obtained through video match analysis. The presence of these correlations affects the methodological choices and set-up to follow during training session provision by the coaches. The relationship established between physical data of exercises incorporating a ball are similar and more relevant to competition. The analysis of game play requires us to gain an understanding and reflect on the transfer that exists between sport specific training and competition and how these can be related. However, the most important aspect to account for is associated to the “functional model” of matches and observing the % differences as displayed in Figure 6.1. Considering that the average metabolic power observed in official matches is about 8.1% higher and the high metabolic power ($m \cdot min^{-1}$) 21.4% compared to training game play, it is important to take these parameters into account. These variables, taking into consideration also the recovery phases cannot be superimposed to match values, since the recovery/pause in training sessions are very important.

The most important methodological reflection must be made on accelerations where this ratio reverses in favor of training with values 11.1% lower during official matches. The reason for this can be explained by the tendency to play on smaller and shallower fields during SSG, with previous findings establishing differences (Fradua *et al.,* 2013; Olthof *et al.,* 2018). The size of the playing areas implemented in SSG highly influence the resultant physical performance of players. Therefore, it is important to maintain principles that respect the averages of the functional model by taking into account the observations made between the essential parameters related to high intensity actions and metabolic power, otherwise even the technical and tactical aspects undertaken in the proposed exercises could create functional overloads in players. The neuromuscular aspect derived from continuous braking and acceleration must be considered as a specific force load, resulting in wider recovery times being required. Interestingly, movements related to high speed, distances covered on average above 16 $km \cdot h^{-1}$, display a 63.5% difference between official games and game play. This highlights that during this specific fundamental part of training this type of run does not occur as commonly as during match-play.

Therefore, the game of soccer needs to careful review and evaluation of the current methods implemented during training. Training exercises are moving towards protocols that are too neuromuscular to the disadvantage of longer runs (in a situational regime/scenario) maybe due to the tactical aspects becoming such an 'obsession'. These changes could compensate for the aspect of high speed, a fundamental factor in open spaces and tactical counter-attack situations and would raise the average metabolic power with the right doses. Further, this is closely linked to accelerations, and needs a minimum speed between 8-12 $km \cdot h^{-1}$ to stimulate the expression, which does not happen in sprints with standstill starts, but more typical of dribbling and technical actions as performed in the SSG.

It has been found that technical performance is maintained despite substantial declines in physical performance during SSG in elite youth players. This finding may have implications for the design of SSG's in elite youth players to ensure physical, technical and tactical capabilities are fully optimised. Modifications in player number, pitch dimensions, rules and coach encouragement, for instance, should all be included by taking into account the main aim of a given session and then have a clear focus on overloading physical or technical elements (Moreira *et al*., 2016). In addition, coaches could anticipate the load resulting from the SSGs and adjust the field size to the player number. By taking into account the field size during SSGs it enables coaches to target the most favourable density for developing expected physical qualities. Calibrating intensity during SSGs would allow coaches to assess each athletic skill in the same conditions of intensity as in the competition (Sangnier *et al*., 2018).

6.5: Conclusion

It is concluded that the high-intensity demands of soccer training are underestimated when assessing the traditional measurements of running speed alone, especially in training sessions or playing positions which are associated with less high-intensity activity. Therefore, estimations of metabolic power better inform the coach of the true demands of a training session (Gaudino *et al*., 2013a). High-intensity demands of SSGs in elite soccer players are systematically underestimated by running speed alone particularly during “small” SSGs and especially for central defenders. Estimations of metabolic power provide a more valid estimation as to the true demands of SSGs (Gaudino *et al*., 2013a).

Many studies have looked at aerobic training and its influence on physical parameters in the game (Helgerud *et al*., 2001; Dupont *et al*., 2004). Considering these new parameters (i.e., metabolic power) it would be interesting to investigate this further by correlating training exercises without the ball to match play, to gain an understanding as to how much a different functional model can influence the intensity/physical performance of the competition expressed in a technical-tactical context. In this research, the small amount of exercises without ball and the identical stimulus for all players, did not allow us to perform such analysis. In the technical-tactical drills such as training game play, the role/position in the specific field has affected performance. A limitation of this study is precisely the absence of analysis on correlations with respect to roles, which could show lower coefficients (r) compared to the whole team. The small number of players analysed in each subgroup did not allow us to deepen the role discourse-specific. Still, a mixture of ball and non-ball training is considered the best formula for any aspect related to neuromuscular recovery, which is mainly stimulated in exercises with SSG type ball.

It would be interesting to further investigate predictive tests of some physiological parameters (e.g. $\dot{V}O_{2max}$, maximal aerobic speed, the energy cost *etc*.) and assess the influence they (in-season) have on the player's ability to express higher metabolic power in the official matches. It must be understood and noted that high intensity in soccer matches is also the result of a technical-tactical strategy of teams. Players who play in roles where running is a fundamental factor almost always manage to express high physical performance values. This discriminates the physiological factor from the effect of performance because of the specific role/system of play, and establishing more information related to players would help us to identify the potential of the required squad formation. Observed differences between generic-running drills and SSG highlight that the specificity of training causes different physiological responses together with time-motion responses due to high speed and accelerations/decelerations which are based on the protocols used (Ade *et al*., 2014). Therefore, when studying player behaviour and performance it is important to consider aspects such as acceleration, as sprints and associated variables (such as mean sprint distance and duration) are less relevant in small areas such as SSG (Casamichana *et al*., 2012), and understanding that accelerations are common. Therefore, the failure to quantify them could lead us to underestimate the amount of high-intensity activity engaged in by players (Varley & Aughey, 2013).

Finally, strength and conditioning professionals ought to consider aerobic fitness in their training program when dealing with professional soccer players. The MP method resulted an interesting approach for tracking external load in male professional soccer players (Manzi *et al*., 2014). Previous findings showed that match activities of a different nature, as per instantaneous interplay between acceleration and speed, are associated with either maximal or submaximal aerobic fitness variables (Stølen *et al*., 2005; Manzi *et al*., 2014). Interindividual aerobic fitness profiles are associated with high MP match categories mainly anaerobic in nature (Osgnach *et al*., 2010) and suggest that successful training at high intensity (sprinting) developing maximal and submaximal aerobic fitness is crucial. Taking this into account is of great interest to practitioners and coaches involved with training prescription in soccer and can help guide them to provide more specific training (Ferrari Bravo *et al*., 2008; Impellizzeri *et al*., 2006). For example, the ability to repeatedly undertake maximal sprints with limited recovery is crucial to expert performance in football (Pullinger *et al*., 2019) and developing an understanding of repeated sprint ability, through a test (Dawson *et al*., 1998; Ferrari Bravo *et al*., 2008; Girard *et al*., 2011; Pullinger *et al*., 2019), which can then be incorporated into concurrent training methods in male professional soccer players will further help with soccer-specific training provision.

Chapter 7: Synthesis of findings

7.1: Fulfilment of aims

The aim of this chapter is to summarise each of the experimental chapters within this thesis and further identify how the main aims of this thesis were met and to ultimately provide recommendations for future research based upon this body of work (Figure 7.1). The specific aims of this thesis were:

1. To assess the accuracy of the measurements calculated through different GPS sampling frequencies and compare them to the gold standard system to determine how much the speed variations are affected (the main aspect of soccer performance). After this, we determined the energy cost (C) to help summarise the physiological variable related to the technical-coordinative component. Two different sets of populations training in different ways were used for analysis to emphasise how the specific training of the soccer player has more important requirements than $\dot{V}O_{2max}$ solely.

2. To calculate the energy cost (C) of running at a constant speed on grass in elite soccer players by applying the average value to the constant term of the 'Minetti equation', which is a central function of the scientific approach proposed by di Prampero for the calculation of metabolic power ($W \cdot kg^{-1}$) in soccer.

3. Applying the constant term of the Minetti's equation on the energy cost (C) that considers the variations in speed. Validating a GPS for the indirect measurement of metabolic power (P_{GPS}) compared with an indirect calorimetry ($P_{\dot{V}O2}$), which is deemed the gold standard. A specific test will be proposed that respects the types of running and intensity present in soccer by applying the 'energetic approach' devised by di Prampero *et al.*, (2005).

4. To investigate the effects of different systems of play in soccer by studying some specific physical parameters and their potential changes between the first and second half. Furthermore, the longitudinal evaluation of a team during a full competitive home season, to observe the relationship between intensity and success (result) through physical match analysis data.

5. To assess possible connections through mathematical correlations of physical data related to training sessions and matches; with the aim of identifying whether the external load, or some information on physical intensity, influences the homologous parameters. The focus was to look at the correlative differences between training without the ball compared to the ball one, to understand where to orientate volumes and intensity from a methodological point of view.

The validity of GPS to determine energy cost in elite soccer: general *vs.* sport-specific

Aim 1 was addressed in Chapter 3 and looked at the validity of GPS data during active movements. The first intention of Chapter 3 was to establish whether the use of laser measurement systems with a sampling frequency of ~100-Hz, would facilitate the accurate assessment of acceleration and deceleration and compare this to a new low cost 10-Hz high-frequency GPS system. The acceleration data obtained by the laser measurement system and GPS was then compared and assessed to establish validity.

Ten male semi-professional soccer players playing at varsity level completed the experimental procedures consisting of 4 different running trials: i) a linear sub-maximal run over a marked 30-m track with low-moderate acceleration and deceleration; ii) a sub-maximal 20-m shuttle run (time and speed were regulated by a sound signal); iii) high-intensity accelerations and decelerations over 50-m; iv) six laps of a measured soccer-specific circuit performed on a synthetic sports surface, where linear run and change of direction were combined.

The main findings of this pilot study were that using a measuring system with an increased 10-Hz GPS sample frequency (rate) provides a valid means of assessing running speed during rapid acceleration and deceleration that occur during linear runs and runs with tight changes of direction compared to a 100-Hz laser system. However, although the 10-Hz GPS is associated with some errors of running speed which are apparent on the linear circuits and equate to about 2 to 4%, it accurately tracks the path of movement and the angular changes occurring during a variety of tasks related to change of direction.

Aim 2 was also addressed in Chapter 3 and compared the different C of straight- and shuttle-running in soccer players *vs.* marathoner runners. The main intention was to assess the differences in training provisions between runners and soccer players, where the focus in soccer players is accelerating and decelerating *vs.* constant-speed straight-running in marathoners and assess this.

The test which was chosen to assess this featured continuous speed changes preventing a truly metabolic steady-state achievement and ensured the investigation of C by applying di Prampero's approach for such purpose.

Ten young professional soccer players playing for the reserve team in the Serie A completed the experimental procedure as part of Group 1. Seven marathon runners completed the experimental procedure as part of Group 2. The experimental study was approached through an observational design and all participants completed one experimental session. Oxygen consumption was evaluated breath-by-breath using a portable gas analyser along with lactate concentration values during both straight- and shuttle-runs. For the calculation of C_r at different constant speeds, each subject ran at different constant speeds on a motorized treadmill to identify the anaerobic threshold speed, steady-state $\dot{V}O_{2max}$ and run-end lactate.

The main findings of this pilot study were that the straight-running energy cost (C_r) of soccer players is significantly greater than runners. Further, soccer players' straight-running C even increases over the sport season but is significantly lower than runners. Shuttle-running economy (C_{sh}) seems to be independent from maximum oxygen consumption ($\dot{V}O_{2max}$). The findings from this study indicate that C highly depends on the practiced sport and its relative training.

Aim 3 was the main aim of Chapter 3 was to an provide up-to-date assessment of C_r in elite soccer players in their ecological setting, a grass soccer pitch, to further determine whether changes in C_r can be established in this population. There is a need to monitor and condition the C_r in elite soccer players, with little research available.

Seventeen male elite, professional soccer players of a national and international level completed the experimental procedure of this study. Each player completed two sessions and underwent an assessment of oxygen consumption ($\dot{V}O_2$) at rest followed by an incremental treadmill run to exhaustion to assess $\dot{V}O_{2max}$. Assessment for C_r was performed on a UEFA standard-size grass soccer pitch. All participants performed an aerobic steady-state, circular run at a speed of 10.29 km·h^{-1} and 6-min in duration. C_r was calculated as the ratio between $\dot{V}O_2$ above its resting value ($\dot{V}O_{2n}$) and the speed (v). The main findings of Chapter 3 were that in elite professional soccer players, the energy cost of straight-running (C_r) on a UEFA standard grass soccer pitch is 4.66 J·kg^{-1}·m^{-1}. It can be established that on grass, C_r assessment provided different estimates of C_r compared to previous findings in the literature, which seem to vary as a function of the surface type as well as the assessed population.

Validity of a new metabolic power algorithm based upon di Prampero's theoretical model of energy cost

Aim 4 was addressed in Chapter 4, using semi-automatic cameras, the global positioning systems (GPS) to collect data related to soccer player performance during match-play and training. With GPS helping to generate information regarding physical differences in players and playing a role in devising more specific training programmes for each playing position, to gain an understanding of the effort required to successfully perform these actions, it is important to understand and incorporate the concept of di Prampero and Osgnach in relation to energy cost (C) and metabolic power (MP). The aim of the study was to investigate the average MP on a soccer-specific test through direct and indirect measurements of oxygen consumption using di Prampero's approach while modifying Minetti's equation of energy cost, while taking into account the statistical approach required to do so.

Thirteen male elite, professional Serie A soccer players of a national and international level completed the experimental procedure of this study. During each trial, participants were fitted with a 10-Hz GPS unit and a portable gas analyser to assess the oxygen uptake directly. At the start and end of each testing session, blood lactate was collected. The maximal oxygen consumption ($\dot{V}O_{2max}$, $mL \cdot kg^{-1} \cdot min^{-1}$) was measured along with determination of C on grass using a soccer-specific high-intensity protocol. The energy costs of soccer-specific exercise (C) and the indirect calculation of metabolic power through GPS (P_{GPS}).

The main findings of Chapter 4 were that shuttle running using low speeds only negatively affects the P_{GPS} by underestimating observed values. Further, this study directly determined physiological demands through GPS derived modelling of the metabolic power; and indicated that in an elite soccer population the GPS metabolic power paradigm is a valid means of determining work rate during activities. Differences in MP expressed as $W \cdot kg^{-1}$ were evident between direct and indirect measurement methods. Data indicated that where there are periods of repeated accelerations and deceleration superimposed on an aerobic background, metabolic power estimates did not differ significantly from directly calculated estimates. The new equation underestimates the metabolic power in elite players by approximately 2.2%.

Metabolic power approach in soccer: a new longitudinal match-performance analysis with a tactical key

Aim 5 was addressed in Chapter 5, with the aim of investigate main volume and intensity of specific physical variables in soccer and its relation to different formations, to establish whether there is a more effective formation and/or a formation more that minimises the between-halves performance decrease. Previous findings related to position-specific performance model studies have shown some limitations over time by not taking into account the different game formations in addition to the different player positions. Additionally, this chapter also wanted to assess whether variables influence the outcome of the first half and final match results and look at the relation to wins, draws, and losses in a professional team over the course of a season.

One hundred and eighty-seven Serie A professional soccer players completed the experimental procedure of this study. Video match analysis was conducted capturing players' movements during matches and was then analysed to create a dataset on each player's physical and technical performance.

The main findings of Chapter 5 were that tactics are influenced by many factors: historical data (previous results against opponent and others) and external factors (e.g. match location, competition, table-rank, referees, weather, *etc*.) in addition to individual and team tactics, physiological, and technical skills factors. Decreases in physical performance (i.e., TDC) and metabolic power (MP) variables were present irrespective of formation in the 2nd half and are not only due to fatigue. A 3-5-2 and 4-4-2 formations are not characterised by such changes and therefore looks like an energy-saving but even performance-preserving formation when analysing physical performance and metabolic expenditure variables.

Training load analysis and physical match performance variables in elite soccer: is there any correlation?

Aim 6 was addressed in Chapter 6, to investigate the correlation between the essential parameters analysed during training sessions and during official matches of elite soccer, while also investigating the 'functional model' proposed in training. With the advancement of technology, a great opportunity is present to combine and compare aspects of physical performance parameters in match-play with the load proposed in training. There is a need to carry out research looking at the metabolic power approach which constitutes of an integrated method potentially useful to track the game and training demands of and further examine the metabolic power responsiveness to training in professional soccer.

Eighteen highly trained male soccer players completed the experimental procedure of this study. All players underwent the same type of training session: game play with different sized pitches, a 5 *vs*. 5 (SSG) and a 10 *vs*. 10 (full-sized) game. The physical and intensity parameters during the training sessions were evaluated using high-frequency GPS. The primary endpoint was to assess the correlation between the physical performance variables during training game play (SSG) and the same parameters observed over the course of a full match. The secondary endpoint was to assess the following physical performance parameters: average metabolic power (MP, $W \cdot kg^{-1}$), distance at high speed (> 16 $km \cdot h^{-1}$), distance at high acceleration (> 2 $m \cdot s^{-2}$), distance at high deceleration (< -2 $m \cdot s^{-2}$) and distance at high metabolic power (> 20 $W \cdot kg^{-1}$) in comparison to the functional model of the same between training and matches.

The main finding of Chapter 6 was that a positive correlation was established between the performance data analysed during the games played in training and locomotor data obtained through video match analysis. High-intensity demands of soccer training are underestimated when assessing the traditional measurements of running speed alone, especially in training sessions or playing positions which are associated with less high-intensity activity. Estimations of metabolic power provide a more valid estimation as to the true demands of SSGs.

APPLICATION OF AN INTEGRATED METABOLIC POWER PARADIGM IN ELITE SOCCER

AIMS

What is the energy cost impact on soccer performance?

Can the 'metabolic power approach' be applied/validated to any kind of physical effort?

What is the relationship between physical parameters in training and competition, compared to the functional model?

CHAPTER 3

Laser measurement systems *vs.* high-frequency GPS would facilitate the accurate assessment of acceleration and deceleration.

10-Hz GPS provides a valid means of assessing running speed during rapid acceleration and deceleration that occur during linear runs and runs with tight changes of direction (errors of running speed about 2 to 4%).

Energy cost of straight (C_r)- and shuttle-running (C_{sh}) in soccer players *vs.* marathoner runners.

The C_r of soccer players is significantly greater than that of runners. Shuttle-running economy (C_{sh}) seems to be independent from maximum oxygen consumption (VO_{2max}). C highly depends on the practiced sport and its relative training.

Up-to-date assessment of C_r in 17 elite professional soccer players in their ecological setting.

C_r on a UEFA standard grass soccer pitch is 4.66 $J \cdot kg^{-1} \cdot m^{-1}$. It can be established that on grass, C_r assessment provided different estimates of C_r compared to previous findings in the literature, which seem to vary as a function of the surface type as well as the assessed population.

CHAPTER 4

Validation of Metabolic Power (MP) on a soccer-specific test through direct and indirect measurements of VO_2 using di Prampero's approach while modifying Minetti's equation in 13 Serie A players.

The MP paradigm is a valid means of determining work rate during activities. Data indicated that where there are periods of repeated *acceleration* and *deceleration* superimposed on an aerobic background, P_{GPS} did not differ significantly from P_{VO2} (the new equation underestimates MP by ~2.2%).

CHAPTER 5

Investigation of the main physical variables in soccer and their relation to different formations in 187 Serie A players.

Decreases in physical performance (i.e., TDC) and MP variables were present irrespective of formation in the 2nd half and are not only due to fatigue. A 3-5-2 and a 4-4-2 formation are not characterised by such changes and therefore is found to be an energy-saving but even 'performance-preserving' formation.

CHAPTER 6

Correlation between the essential parameters analysed during training sessions and during matches of 18 elite soccer players, while also investigating the 'functional model' proposed in training.

Positive correlation was established between the performance data analysed during the games played in training and the locomotor data obtained through video match analysis. Estimations of MP provide a more valid estimation as to the true demands of SSGs.

PRACTICAL APPLICATIONS

Applying a model that evaluates matches and incorporates training variables through biomechanical and energy intuition is easy to apply.

Info obtained from an MP approach can help describe the activity/intensity present in the game of soccer and provides a new scenario of analysis and observation.

A modern-day data scientist who wants to get closer to understanding the game, must assess the purely physical data (response) and consider the technical-tactical aspect (cause) during match-play.

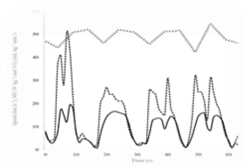


Figure 7.1. Infographic on aims, synthesis of findings and practical applications.

7.2: Conclusions and recommendations for future research

The objective of this thesis was to further determine the concept of training load in soccer. To achieve this, the starting point must be the soccer-specific study of movement and its peculiarities. The technology that is available nowadays offers us the possibility to indirectly measure the basic physiological magnitudes to help guide training and provide a more in-depth understanding about the physical aspects required during a game. Energy cost (C) is an index that sums up physiology and technique requirements by explaining how sport specific training can modify some parameters closely related to efficiency in players. The study of this in soccer players is a fundamental way to apply a value to mathematical models and equations that consider the daily activity carried out, such as accelerations, decelerations and changes of direction. This further leads to the economy of running at constant speeds in the opposite direction.

Applying a model that evaluates matches and incorporates training variables through biomechanical and energy intuition is easy to apply when the kinematic data is available. Through the study of direct measurement of oxygen consumption ($P_{\dot{V}O2}$) and the calculated metabolic power (P_{GPS}) and its differences, it has been possible to widen the vision of the external training load by rationally integrating the information derived from speed alone with those related to its variations over time. $\dot{V}O_{2max}$ explains only 24% of P_{GPS} (r = 0.49); that is if we expected players with a higher maximal oxygen consumption to have a consequent higher metabolic power, and therefore make an assessment error, given that there are subjects capable of expressing P_{GPS} of ~15.7 W·kg^{-1} with both 70 and 57 mL·kg^{-1}·min^{-1}, therefore with 23% reduction in aerobic power (maximal oxygen uptake). A high $P_{\dot{V}O2}$ does not necessarily imply a high P_{GPS}, which represents the external load: the effect on the speed data calculated through the movements tracked by the GPS.

Ultimately there are three issues to be methodologically expanded:

i) the extra energy, reasoning on the use of 100-Hz tri-axial accelerometers together with the correct mathematical filters. Buchheit & Simpson (2017) address this discourse by arguing that accelerometers are practical assessment methods to quantify stride variables when used indoors (i.e., no GPS signal is required), therefore allowing the use for intermittent team-sports (e.g., basketball, handball). All of this could improve the assessment of eventual muscle strength deficits in players, leading to progress in the field of injury recovery (Buchheit & Simpson 2017; Buchheit *et al*., 2015). Furthermore Osgnach *et al*. (unpublished data) are focusing on a study related to 'Muscle Power' (GPEXE ©, Exelio Srl, Udine, Italy), with the aim of considering the greater muscular load of the braking activities (decelerations) compared to those in observed acceleration. All that could reduce the underestimation of P_{GPS} compared to $P_{\dot{V}O2}$, evaluating the addition of a small energy surplus deriving from neuromuscular fatigue. Technologies such as surface electromyographs in correlation with current estimates of metabolic power could be decisive for developing new energy cost equations (with more attention to e.g. decelerations, CoD *etc*.) according to Buchheit *et al*. (2015) and Hader *et al*. (2016).

The reason why it was chosen not to implement the update to the concept of equivalent slope (Minetti *et al*., 2018), in addition to the changes proposed by di Prampero and Osgnach (2018) on the inclusion of a lower energy cost for the walking phases (C_w), is dictated by the fact that the original equation (Minetti *et al*., 2002), with small adjustments as presented Chapter 4, is already able to estimate the EE of an intermittent exercise (Bangsbo, 1994b). These changes, if applied, would make the metabolic power of soccer matches lower by at least ~14% (di Prampero and Osgnach, 2018), giving rationale to the limitations on the metabolic power concept raised by opponents of the concept (Buchheit & Simpson, 2017).

ii) The performance model in the choice of tests that we want to validate together with calculations on energetics of muscular exercise (Chapter 4). In support of this, Brown *et al*. (2016) mentioned that using other criterion procedures which can measure both anaerobic and aerobic EE directly can help the assessment of validating the approach. This concept has been found to work positively in this study.

If we wanted to recommend improvements to our study, we would opt for: 1) the insertion of the ball in the soccer-specific circuit for a maximum of 5-10s per lap (e.g. sprint with ball conduction or 5-s of ball control and passing/or shooting *etc*.); 2) the inclusion of at least a couple of walking/slow running phases given the active nature of the recovery (5-10 $W \cdot kg^{-1}$) in soccer; 3) the increase of the sample to be studied in order to statistically understand what the relation of the P_{GPS} is when calculated compared to the P_{VO2} measurement; 4) adding a camera at the start to record the time during the maximum triangle performed at each lap, in order to obtain a series of times to assess the minute-by-minute performance decrement (Fitzsimmons *et al*., 1993; Bishop & Spencer, 2004). This test could be an alternative to the various repeated sprint ability (RSA) tests proposals found in the literature (Bishop *et al*., 2001; Haugen *et al*., 2014; Haugen & Buchheit, 2016), to study more specifically the 'true' RSA, by alternating the maximal bouts with runs and recoveries of various kinds, to simulate the intermittent scenario of the game.

These are closely linked to the decisive role of the energy cost (C) which obviously in the soccer-specific circuit proposed by us is ~38% higher than C_r on the grass at constant speed ($6.41 > 4.66\ J \cdot kg^{-1} \cdot m^{-1}$, see Chapter 4). It is essential to train with specificity and look for the economy of the game's movements ‘throughout the game’ and not obtaining a greater efficiency of the running technique (i.e., athletics), which would lead to an improvement of the C_r, which as seen by Buglione & di Prampero (2012) gets worse during the soccerer's competitive season. The biomechanics of running is sport-specific as training and tests must be.

iii) The application of the 'metabolic power' approach to video match- and time-motion analysis with the same equations and algorithms used by the GPS software for training load analysis, represents the future of soccer, with the possibility of assessing metabolic performance of the player every game, studying the trend with respect to the loads incurred in training. The uniformity and homologation of the algorithms would really represent a turning point to compare training methods/philosophies (i.e., traditional, tactical periodization) and different championship competitions (similarities and differences with respect to the presence or absence of cup tournaments). Extending the discussion, the utility would also fall on the choice of the players during the transfer window updating database useful for soccer scouting, match analysis and transfer dynamic (such as e.g. Wyscout, InStat, STATS, trasfermarkt *etc*.), integrating over the technical-tactical information, the physical performance and the history injuries, looking for the keystones for understanding his official performance parameters together with training loads carried out in the belonging club, through the same 'integrated soccer language' (Azzone & Lorenzon, 2019).

However, despite its some of the limitations, the information can better describe the activity currently present in the game of soccer and its concept of intensity and provides a further opening to the scenario of analysis and observation. Player practice on the field imposes the application of these models to the daily activity of analysis of training sessions both, with and without the ball. In the last few years, with games having almost total coverage of video tracking systems in the stadiums and the possibility of applying high-frequency GPS to the players during their weekly microcycles, the comparison and the periodization of training has become a great interest among the professionals working within this sector.

A modern-day data scientist who wants to get closer and closer to fully understanding the game, cannot untie the purely physical data (response) from the technical-tactical aspect (cause) during match-play. Considering soccer is a situational sport, its performance is mainly influenced by the need for strategical and tactical developments in the field, which could also impose moments of pause/rest between repeated high intensity actions. The final aim of this thesis was to precisely verify how the system of play could affect performance and how the latter was not necessarily linked to the result. Furthermore, having training session data available, it was necessary to study how the intensity of the exercises with the ball were more correlated than the 'dry activity' (no ball) with some of the physical parameters analysed during competition. A demonstration that the specificity has a much stronger correlation to game play compared to the physical activity with displays more general characteristics.

In the future it would be desirable to use large data sets through machine learning and data mining systems so that the spectrum of analysis can be further expanded. This will help with the association of not only "static information" to the physical data, such as: role, system of play, result, percentage of ball possession *etc*., but also "dynamic information", such as the flow of tactical attitudes tagged through video match analysis. This would further lead to the understanding and explanation of observed physical data according to the specific moment/action in the game and help summarize the information that is useful for choosing a winning game strategy for the manager.

Some of the outcomes of this research are important in relation to the following soccer performance issues:

a. A new energy cost constant for running on UEFA standard grass pitch in elite soccer players has been quantified for the first time.

b. A metabolic power paradigm (C equation, Minetti *et al.*, 2002 modified) with direct specificity to elite soccer players is now available and validated.

c. Application of this new metabolic power paradigm to match play data derived from both video match-analysis and integrated GPS technology has highlighted limitations in the use of current speed and distance match-analysis paradigms applied to objectively quantified soccer performance (Castagna *et al.*, 2014; Gaudino *et al.*, 2014a; Martínez-Cabrera & Núñez-Sánchez, 2018; Beato *et al.*, 2018b). These limitations fail to reflect the quantity and intensity of the metabolic load applied during match play by up to at least ~30%.

d. Furthermore, we propose to establish metabolic power requirements during competitive match play for different positional roles, tactical system of play, how metabolic changes over the course of a season, and opposition style of play, providing a normative reference ranges for metabolic power and energy expenditure estimates. These estimates may be (are been) utilised to consider general/specific thresholds of effort required for the regulation of training intensity, and importantly training load particularly where training may be orchestrated and assessed via GPS monitoring (Manzi *et al*., 2014; Castagna *et al*., 2017; Hoppe *et al*., 2017; Martínez-Cabrera & Núñez-Sánchez, 2018).

e. These normative ranges may be particularly useful in assessing the efficacy of current training regimen i.e., the small sided game which is a mainstay of physical and technical preparation in soccer (Gaudino *et al*., 2014).

References

Achten, J. and Jeukendrup, A.E., (2003) Heart rate monitoring: applications and limitations. *Sports Medicine (Auckland, N.Z.)*, 337, pp.517–538.

Ade, J.D., Harley, J.A. and Bradley, P.S., (2014) Physiological response, time-motion characteristics, and reproducibility of various speed-endurance drills in elite youth soccer players: small-sided games versus generic running. *International Journal of Sports Physiology and Performance*, 93, pp.471–479.

Akenhead, R., French, D., Thompson, K.G. and Hayes, P.R., (2014) The acceleration dependent validity and reliability of 10 Hz GPS. *Journal of Science and Medicine in Sport*, 175, pp.562–566.

Akenhead, R. and Nassis, G.P., (2016) Training Load and Player Monitoring in High-Level Soccer: Current Practice and Perceptions. *International Journal of Sports Physiology and Performance*, 115, pp.587–593.

Alexandre, D., da Silva, C.D., Hill-Haas, S., Wong, D.P., Natali, A.J., De Lima, J.R.P., Bara Filho, M.G.B., Marins, J.J.C.B., Garcia, E.S. and Karim, C., (2012) Heart rate monitoring in soccer: interest and limits during competitive match play and training, practical application. *Journal of Strength and Conditioning Research*, 2610, pp.2890–2906.

Althoff, K. and Hennig, E.M., (2013) Performance differences between female and male soccer players - recommendations for shoe designs. *Footwear Science*, 5sup1, pp.S5–S6.

Altman, D.G., Machin, D., Bryant, T.N. and Gardner, M.J., (2000) *Statistics with confidence: confidence intervals and statistical guidelines*. [online] BMJ Books. Available at: https://eprints.soton.ac.uk/393017/ [Accessed 20 May 2019].

Ardigò, L.P., Padulo, J., Zuliani, A. and Capelli, C., (2015) A low-cost method for estimating energy expenditure during soccer refereeing. *Journal of Sports Sciences*, 3317, pp.1853–1858.

Arellano, C.J. and Kram, R., (2014) Partitioning the metabolic cost of human running: a task-by-task approach. *Integrative and Comparative Biology*, 546, pp.1084–1098.

Arsac, L.M. and Locatelli, E., (2002) Modeling the energetics of 100-m running by using speed curves of world champions. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, 925, pp.1781–1788.

Aughey, R.J., (2011) Applications of GPS technologies to field sports. *International Journal of Sports Physiology and Performance*, 63, pp.295–310.

Aughey, R.J. and Falloon, C., (2010) Real-time versus post-game GPS data in team sports. *Journal of Science and Medicine in Sport*, 133, pp.348–349.

Azzone, V. and Lorenzon, F., (2019) Integrare i dati fisici con quelli tecnico-tattici. *Notiziario del Settore Tecnico F.I.G.C.*, 2, pp.14–36.

Bailey, J., (2017) Analysis of Human Movement Patterns during Endurance Running. *UNLV Theses, Dissertations, Professional Papers, and Capstones*. [online] Available at: https://digitalscholarship.unlv.edu/thesesdissertations/3069.

Balducci, P., Clémençon, M., Robin, T. and Hautier, C., (2017) The Calculation of the Uphill Energy Cost of Running from the Level Energy Cost of Running in a

Heterogeneous Group of Mountain Ultra Endurance Runners. *Asian Journal of Sports Medicine*, 8, pp.1–4.

Bangsbo, J., (1994a) *Fitness Training in Soccer: A Scientific Approach*. August Krogh Institute, University of Copenhagen, pp.112–113.

Bangsbo, J., (1994b) The physiology of soccer--with special reference to intense intermittent exercise. *Acta Physiologica Scandinavica. Supplementum*, 619, pp.1–155.

Bangsbo, J., (1996) *Yo-Yo test*. Kells, Ancona.

Bangsbo, J., Mohr, M. and Krustrup, P., (2006) Physical and metabolic demands of training and match-play in the elite soccer player. *Journal of Sports Sciences*, 247, pp.665–674.

Barbero-Alvarez, J.C., Coutts, A., Granda, J., Barbero-Alvarez, V. and Castagna, C., (2010) The validity and reliability of a global positioning satellite system device to assess speed and repeated sprint ability (RSA) in athletes. *Journal of Science and Medicine in Sport*, 132, pp.232–235.

Barbero-Alvarez, J.C., Soto, V.M., Barbero-Alvarez, V. and Granda-Vera, J., (2008) Match analysis and heart rate of futsal players during competition. *Journal of Sports Sciences*, 261, pp.63–73.

Bastida Castillo, A., Gómez Carmona, C.D., De la Cruz Sánchez, E. and Pino Ortega, J., (2018) Accuracy, intra- and inter-unit reliability, and comparison between GPS and UWB-based position-tracking systems used for time-motion analyses in soccer. *European Journal of Sport Science*, 184, pp.450–457.

Batterham, A.M., (2004) *Commentary on bias in Bland-Altman but not regression validity analyses*. [online] Sportscience. Available at:

http://link.galegroup.com/apps/doc/A165819924/AONE?sid=googlescholar [Accessed 25 Apr. 2019].

Batterham, A.M. and Hopkins, W.G., (2006) Making meaningful inferences about magnitudes. *International Journal of Sports Physiology and Performance*, 11, pp.50–57.

Beato, M., Bartolini, D., Ghia, G. and Zamparo, P., (2016) Accuracy of a 10 Hz GPS Unit in Measuring Shuttle Velocity Performed at Different Speeds and Distances (5 - 20 M). *Journal of Human Kinetics*, 54, pp.15–22.

Beato, M., Devereux, G. and Stiff, A., (2018a) Validity and Reliability of Global Positioning System Units (STATSports Viper) for Measuring Distance and Peak Speed in Sports. *Journal of Strength and Conditioning Research*, 3210, pp.2831–2837.

Beato, M., Jamil, M. and Devereux, G., (2018b) Reliability of internal and external load parameters in recreational soccer (soccer) for health. *Research in Sports Medicine (Print)*, 262, pp.244–250.

Beltz, N.M., Gibson, A.L., Janot, J.M., Kravitz, L., Mermier, C.M. and Dalleck, L.C., (2016) Graded Exercise Testing Protocols for the Determination of VO2max: Historical Perspectives, Progress, and Future Considerations. *Journal of Sports Medicine (Hindawi Publishing Corporation)*, 2016, p.3968393.

Beneke, R. and Hütler, M., (2005) The effect of training on running economy and performance in recreational athletes. *Medicine and Science in Sports and Exercise*, 3710, pp.1794–1799.

Bishop, D. and Spencer, M., (2004) Determinants of repeated-sprint ability in well-trained team-sport athletes and endurance-trained athletes. *The Journal of Sports Medicine and Physical Fitness*, 441, pp.1–7.

Bishop, D., Spencer, M., Duffield, R. and Lawrence, S., (2001) The validity of a repeated sprint ability test. *Journal of Science and Medicine in Sport*, 41, pp.19–29.

Bland, J.M., (2009) *How do I estimate limits of agreement when the mean or SD of differences is not constant?* [online] Available at: https://www-users.york.ac.uk/~mb55/meas/glucose.htm [Accessed 20 May 2019].

Bland, J.M. and Altman, D.G., (1986) Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet (London, England)*, 1, pp.307–310.

Bland, J.M. and Altman, D.G., (1995) Comparing methods of measurement: why plotting difference against standard method is misleading. *Lancet (London, England)*, 346, pp.1085–1087.

Bland, J.M. and Altman, D.G., (1999) Measuring agreement in method comparison studies. *Statistical Methods in Medical Research*, 82, pp.135–160.

Bland, J.M. and Altman, D.G., (2003) Applying the right statistics: analyses of measurement studies. *Ultrasound in Obstetrics & Gynecology: The Official Journal of the International Society of Ultrasound in Obstetrics and Gynecology*, 221, pp.85–93.

Bourdon, P.C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M.C., Gabbett, T.J., Coutts, A.J., Burgess, D.J., Gregson, W. and Cable, N.T., (2017) Monitoring Athlete Training Loads: Consensus Statement. *International Journal of Sports Physiology and Performance*, 12Suppl 2, pp.S2161–S2170.

Bowen, L., Gross, A.S., Gimpel, M. and Li, F.-X., (2017) Accumulated workloads and the acute:chronic workload ratio relate to injury risk in elite youth football players. *British Journal of Sports Medicine*, 515, pp.452–459.

Bradley, P.S. and Ade, J.D., (2018) Are Current Physical Match Performance Metrics in Elite Soccer Fit for Purpose or Is the Adoption of an Integrated Approach Needed? *International Journal of Sports Physiology and Performance*, 135, pp.656–664.

Bradley, P.S., Carling, C., Archer, D., Roberts, J., Dodds, A., Di Mascio, M., Paul, D., Diaz, A.G., Peart, D. and Krustrup, P., (2011) The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *Journal of Sports Sciences*, 298, pp.821–830.

Bradley, P.S., Dellal, A., Mohr, M., Castellano, J. and Wilkie, A., (2014) Gender differences in match performance characteristics of soccer players competing in the UEFA Champions League. *Human Movement Science*, 33, pp.159–171.

Bradley, P.S., Di Mascio, M., Peart, D., Olsen, P. and Sheldon, B., (2010) High-intensity activity profiles of elite soccer players at different performance levels. *Journal of Strength and Conditioning Research*, 249, pp.2343–2351.

Bradley, P.S., Lago-Peñas, C., Rey, E. and Gomez Diaz, A., (2013) The effect of high and low percentage ball possession on physical and technical profiles in English FA Premier League soccer matches. *Journal of Sports Sciences*, 3112, pp.1261–1270.

Bradley, P.S., Sheldon, W., Wooster, B., Olsen, P., Boanas, P. and Krustrup, P., (2009) High-intensity running in English FA Premier League soccer matches. *Journal of Sports Sciences*, 272, pp.159–168.

Brown, D.M., Dwyer, D.B., Robertson, S.J. and Gastin, P.B., (2016) Metabolic Power Method: Underestimation of Energy Expenditure in Field-Sport Movements Using a Global Positioning System Tracking System. *International Journal of Sports Physiology and Performance*, 118, pp.1067–1073.

Buchheit, M., (2014) Monitoring training status with HR measures: do all roads lead to Rome? *Frontiers in Physiology*, 5, p.73.

Buchheit, M., Al Haddad, H., Simpson, B.M., Palazzi, D., Bourdon, P.C., Di Salvo, V. and Mendez-Villanueva, A., (2014a) Monitoring accelerations with GPS in soccer: time to slow down? *International Journal of Sports Physiology and Performance*, 93, pp.442–445.

Buchheit, M., Allen, A., Poon, T.K., Modonutti, M., Gregson, W. and Di Salvo, V., (2014b) Integrating different tracking systems in soccer: multiple camera semi-automatic system, local position measurement and GPS technologies. *Journal of Sports Sciences*, 3220, pp.1844–1857.

Buchheit, M., Gray, A. and Morin, J.-B., (2015) Assessing Stride Variables and Vertical Stiffness with GPS-Embedded Accelerometers: Preliminary Insights for the Monitoring of Neuromuscular Fatigue on the Field. *Journal of Sports Science & Medicine*, 144, pp.698–701.

Buchheit, M., Manouvrier, C., Cassirame, J. and Morin, J.-B., (2015a) Monitoring Locomotor Load in Soccer: Is Metabolic Power, Powerful? *International Journal of Sports Medicine,* 3614, pp.1149–1155.

Buchheit, M. and Simpson, B.M., (2017) Player-Tracking Technology: Half-Full or Half-Empty Glass? *International Journal of Sports Physiology and Performance*, 12Suppl 2, pp.S235–S241.

Buglione, A., Lazzer, S., Colli, R., Introini, E. and di Prampero, P.E., (2011) Energetics of best performances in elite kayakers and canoeists. *Medicine and Science in Sports and Exercise,* 435, pp.877–884.

Buglione, A. and di Prampero, P.E., (2012) *Energy cost of elite soccer players before and during season*. Poster session presented at the XXXII World Congress of Sports Medicine, Rome, Italy.

Buglione, A. and di Prampero, P.E., (2013) The energy cost of shuttle running. *European Journal of Applied Physiology*, 1136, pp.1535–1543.

Cardinale, M. and Varley, M.C., (2017) Wearable Training-Monitoring Technology: Applications, Challenges, and Opportunities. *International Journal of Sports Physiology and Performance*, 12Suppl 2, pp.S255–S262.

Carling, C., (2010) Analysis of physical activity profiles when running with the ball in a professional soccer team. *Journal of Sports Sciences*, 283, pp.319–326.

Carling, C., (2011) Influence of opposition team formation on physical and skill-related performance in a professional soccer team. *European Journal of Sport Science*, 113, pp.155–164.

Carling, C., (2013) Interpreting physical performance in professional soccer match-play: should we be more pragmatic in our approach? *Sports Medicine (Auckland, N.Z.)*, 438, pp.655–663.

Carling, C., Bloomfield, J., Nelsen, L. and Reilly, T., (2008) The role of motion analysis in elite soccer: contemporary performance measurement techniques and work rate data. *Sports Medicine (Auckland, N.Z.)*, 3810, pp.839–862.

Carling, C. and Dupont, G., (2011) Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *Journal of Sports Sciences*, 291, pp.63–71.

Casamichana, D., Castellano, J., Calleja-Gonzalez, J., San Román, J. and Castagna, C., (2013) Relationship between indicators of training load in soccer players. *Journal of Strength and Conditioning Research*, 272, pp.369–374.

Casamichana, D., Castellano, J. and Castagna, C., (2012) Comparing the physical demands of friendly matches and small-sided games in semiprofessional soccer players. *Journal of Strength and Conditioning Research*, 263, pp.837–843.

Casanova, F., Garganta, J., Silva, G., Alves, A., Oliveira, J. and Williams, A.M., (2013) Effects of prolonged intermittent exercise on perceptual-cognitive processes. *Medicine and Science in Sports and Exercise*, 458, pp.1610–1617.

Castagna, C., Varley, M., Póvoas, S.C.A. and D'Ottavio, S., (2017) Evaluation of the Match External Load in Soccer: Methods Comparison. *International Journal of Sports Physiology and Performance*, 124, pp.490–495.

Castellano, J., Alvarez-Pastor, D. and Bradley, P.S., (2014) Evaluation of research using computerised tracking systems (Amisco and Prozone) to analyse physical performance in elite soccer: a systematic review. *Sports Medicine (Auckland, N.Z.)*, 445, pp.701–712.

Castellano, J., Blanco-Villaseñor, A. and Alvarez, D., (2011) Contextual variables and time-motion analysis in soccer. *International Journal of Sports Medicine*, 326, pp.415–421.

Castellano, J. and Casamichana, D., (2013) Differences in the Number of Accelerations Between Small-Sided Games and Friendly Matches in Soccer. *Journal of Sports Science & Medicine*, 121, pp.209–210.

Castellano, J., Casamichana, D., Calleja-González, J., Román, J.S. and Ostojic, S.M., (2011a) Reliability and Accuracy of 10 Hz GPS Devices for Short-Distance Exercise. *Journal of Sports Science & Medicine*, 101, pp.233–234.

Castellano, J., Puente, A., Echeazarra, I. and Casamichana, D., (2015) Influence of the number of players and the relative pitch area per player on heart rate and physical demands in youth soccer. *Journal of Strength and Conditioning Research*, 296, pp.1683–1691.

Chmura, P., Konefał, M., Chmura, J., Kowalczuk, E., Zając, T., Rokita, A. and Andrzejewski, M., (2018) Match outcome and running performance in different intensity ranges among elite soccer players. *Biology of Sport*, 352, pp.197–203.

Clemente, F., Couceiro, M., Martins, F., Ognyanova Ivanova, M. and Mendes, R., (2013) Activity Profiles of Soccer Players During the 2010 World Cup. *Journal of human kinetics*, 38, pp.201–11.

Colli, R., Buglione, A., Introini, E. and D'Ottavio, S., (2007) L'allenamento intermittente tra scienza e prassi. *SDS*, 72, pp.45–52.

Conley, D.L. and Krahenbuhl, G.S., (1980) Running economy and distance running performance of highly trained athletes. *Medicine and Science in Sports and Exercise*, 125, pp.357–360.

Coutts, A.J. and Duffield, R., (2010) Validity and reliability of GPS devices for measuring movement demands of team sports. *Journal of Science and Medicine in Sport*, 131, pp.133–135.

Coutts, A.J., Kempton, T., Sullivan, C., Bilsborough, J., Cordy, J. and Rampinini, E., (2015) Metabolic power and energetic costs of professional Australian Football match-play. *Journal of Science and Medicine in Sport*, 182, pp.219–224.

Coutts, A.J., Rampinini, E., Marcora, S.M., Castagna, C. and Impellizzeri, F.M., (2009) Heart rate and blood lactate correlates of perceived exertion during small-sided soccer games. *Journal of Science and Medicine in Sport*, 121, pp.79–84.

Cummins, C., Gray, A., Shorter, K., Halaki, M. and Orr, R., (2016) Energetic and Metabolic Power Demands of National Rugby League Match-Play. *International Journal of Sports Medicine*, 377, pp.552–558.

Dalen, T., Sandmæl, S., Stevens, T.G.A., Hjelde, G.H., Kjøsnes, T.N. and Wisløff, U., (2019) Differences in Acceleration and High-Intensity Activities Between Small-Sided Games and Peak Periods of Official Matches in Elite Soccer Players. *Journal of Strength and Conditioning Research*. Advance online publication. doi:10.1519/JSC.0000000000003081

da Mota, G.R., Thiengo, C.R., Gimenes, S.V. and Bradley, P.S., (2016) The effects of ball possession status on physical and technical indicators during the 2014 FIFA World Cup Finals. *Journal of Sports Sciences*, 346, pp.493–500.

da Silva, J.F., Guglielmo, L.G.A. and Bishop, D., (2010) Relationship between different measures of aerobic fitness and repeated-sprint ability in elite soccer players. *Journal of Strength and Conditioning Research*, 248, pp.2115–2121.

Datson, N., Hulton, A., Andersson, H., Lewis, T., Weston, M., Drust, B. and Gregson, W., (2014) Applied physiology of female soccer: an update. *Sports Medicine (Auckland, N.Z.)*, 449, pp.1225–1240.

Davis, J.A. and Brewer, J., (1993) Applied physiology of female soccer players. *Sports Medicine (Auckland, N.Z.)*, 163, pp.180–189.

Dawson, B., Fitzsimons, M., Green, S., Goodman, C., Carey, M. and Cole, K., (1998) Changes in performance, muscle metabolites, enzymes and fibre types after short sprint training. *European Journal of Applied Physiology and Occupational Physiology*, 782, pp.163–169.

Delaney, J.A., Duthie, G.M., Thornton, H.R. and Pyne, D.B., (2018) Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index. *Science and Medicine in Football*, 22, pp.149–156.

Delaney, J.A., Duthie, G.M., Thornton, H.R., Scott, T.J., Gay, D. and Dascombe, B.J., (2016) Acceleration-Based Running Intensities of Professional Rugby League Match Play. *International Journal of Sports Physiology and Performance*, 116, pp.802–809.

Di Mascio, M., Ade, J. and Bradley, P.S., (2015) The reliability, validity and sensitivity of a novel soccer-specific reactive repeated-sprint test (RRST). *European Journal of Applied Physiology*, 11512, pp.2531–2542.

Dolci, F., Hart, N.H., Kilding, A., Chivers, P., Piggott, B. and Spiteri, T., (2018) Movement Economy in Soccer: Current Data and Limitations. *Sports*, [online] 64. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6316880/ [Accessed 29 Jul. 2019].

Drust, B., Atkinson, G. and Reilly, T., (2007) Future perspectives in the evaluation of the physiological demands of soccer. *Sports Medicine (Auckland, N.Z.)*, 379, pp.783–805.

Drust, B., Waterhouse, J., Atkinson, G., Edwards, B. and Reilly, T., (2005) Circadian rhythms in sports performance--an update. *Chronobiology International*, 221, pp.21–44.

Dubois, R., Paillard, T., Lyons, M., Mcgrath, D., Maurelli, O. and Prioux, J., (2017) Running and Metabolic Demands of Elite Rugby Union Assessed Using Traditional, Metabolic Power, and Heart Rate Monitoring Methods. *Journal of sports science & medicine*, 16, pp.84–92.

Duffield, R., Reid, M., Baker, J. and Spratford, W., (2010) Accuracy and reliability of GPS devices for measurement of movement patterns in confined spaces for court-based sports. *Journal of Science and Medicine in Sport*, 135, pp.523–525.

di Prampero, P.E., (1981) Energetics of muscular exercise. *Reviews of Physiology, Biochemistry and Pharmacology*, 89, pp.143–222.

di Prampero, P.E., (1986) The energy cost of human locomotion on land and in water. *International Journal of Sports Medicine*, 72, pp.55–72.

di Prampero, P.E., Botter, A. and Osgnach, C., (2015) The energy cost of sprint running and the role of metabolic power in setting top performances. *European Journal of Applied Physiology*, 1153, pp.451–469.

di Prampero, P.E. and Ferretti, G., (1999) The energetics of anaerobic muscle metabolism: a reappraisal of older and recent concepts. *Respiration Physiology*, 1182, pp.103–115.

di Prampero, P.E., Fusi, S., Sepulcri, L., Morin, J.B., Belli, A. and Antonutto, G., (2005) Sprint running: a new energetic approach. *The Journal of Experimental Biology*, 208Pt 14, pp.2809–2816.

di Prampero, P.E. and Osgnach, C., (2018) Metabolic Power in Team Sports - Part 1: An Update. *International Journal of Sports Medicine*, 398, pp.581–587.

di Prampero, P.E., Peeters, L. and Margaria, R., (1973) Alactic O 2 debt and lactic acid production after exhausting exercise in man. *Journal of Applied Physiology*, 345, pp.628–632.

di Prampero, P.E., Salvadego, D., Fusi, S. and Grassi, B., (2009) A simple method for assessing the energy cost of running during incremental tests. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, 1074, pp.1068–1075.

Di Salvo, V., Adam, C., Barry, M. and Cardinale, M., (2006) Validation of Prozone ®: A new video-based performance analysis system. *International Journal of Performance Analysis in Sport*, 6, pp.108–119.

Di Salvo, V., Baron, R., González-Haro, C., Gormasz, C., Pigozzi, F. and Bachl, N., (2010) Sprinting analysis of elite soccer players during European Champions League and UEFA Cup matches. *Journal of Sports Sciences*, 2814, pp.1489–1494.

Di Salvo, V., Baron, R., Tschan, H., Calderon Montero, F.J., Bachl, N. and Pigozzi, F., (2007) Performance characteristics according to playing position in elite soccer. *International Journal of Sports Medicine*, 283, pp.222–227.

Di Salvo, V., Gregson, W., Atkinson, G., Tordoff, P. and Drust, B., (2009) Analysis of high intensity activity in Premier League soccer. *International Journal of Sports Medicine*, 303, pp.205–212.

Di Salvo, V. and Pigozzi, F., (1998) Physical training of soccer players based on their positional rules in the team. Effects on performance-related factors. *The Journal of Sports Medicine and Physical Fitness*, 384, pp.294–297.

Di Salvo, V., Pigozzi, F., González-Haro, C., Laughlin, M.S. and De Witt, J.K., (2013) Match performance comparison in top English soccer leagues. *International Journal of Sports Medicine*, 346, pp.526–532.

Doğramaci, S. and Watsford, M., (2006) A comparison of two different methods for time-motion analysis in team sports. *International Journal of Performance Analysis in Sport*, 6, pp.73–83.

Domene, A.M., (2013) Evaluation of movement and physiological demands of full-back and center-back soccer players using global positioning systems. *Journal of Human Sport and Exercise,* 84, pp.1015–1028.

Dupont, G., Akakpo, K. and Berthoin, S., (2004) The effect of in-season, high-intensity interval training in soccer players. *Journal of Strength and Conditioning Research*, 183, pp.584–589.

Dwyer, D.B. and Gabbett, T.J., (2012) Global positioning system data analysis: velocity ranges and a new definition of sprinting for field sport athletes. *Journal of Strength and Conditioning Research*, 263, pp.818–824.

Edgecomb, S.J. and Norton, K.I., (2006) Comparison of global positioning and computer-based tracking systems for measuring player movement distance during Australian football. *Journal of Science and Medicine in Sport*, 91–2, pp.25–32.

Edvardsen, E., Hem, E. and Anderssen, S.A., (2014) End criteria for reaching maximal oxygen uptake must be strict and adjusted to sex and age: a cross-sectional study. *PLoS ONE*, 9(1), p.e85276.

Ekblom, B., (1986) Applied physiology of soccer. *Sports Medicine (Auckland, N.Z.)*, 31, pp.50–60.

Evaggelos, M., Papadopoulos, C., Konstantinos, M., Ioannis, G., Bekris, E. And Aristomenis, S., (2012) The effect of training, playing position, and duration of participation on aerobic capacity in soccer players. *Journal of Physical Education and Sport*, 12, pp.188-194.

Felipe, J.L., Garcia-Unanue, J., Viejo-Romero, D., Navandar, A. and Sánchez-Sánchez, J., (2019) Validation of a Video-Based Performance Analysis System (Mediacoach®) to Analyze the Physical Demands during Matches in LaLiga. *Sensors (Basel, Switzerland)*, 1919.

Fernandez-Navarro, J., Fradua, L., Zubillaga, A. and McRobert, A.P., (2018) Influence of contextual variables on styles of play in soccer. *International Journal of Performance Analysis in Sport*, 183, pp.423–436.

Ferrari Bravo, D., Impellizzeri, F.M., Rampinini, E., Castagna, C., Bishop, D. and Wisloff, U., (2008) Sprint vs. interval training in soccer. *International Journal of Sports Medicine*, 298, pp.668–674.

Filetti, C., Ruscello, B., D'Ottavio, S. and Fanelli, V., (2017) A Study of Relationships Among Technical, Tactical, Physical Parameters and Final Outcomes in Elite Soccer Matches as Analyzed by a Semiautomatic Video Tracking System. *Perceptual and Motor Skills*, 124, pp.601–620.

Fitzsimmons, M., Dawson, B., Ward, D., Wilkinson, A., Dawson-Hughes, B., Ware, D., Wilkinson, A.W. and Fitzsimons, M., (1993) Cycling and running tests of repeated sprint ability. [online] Available at: https://www.scienceopen.com/document?vid=e7b9664d-c14c-4f1d-a41f-aeb5a0c5f8bc [Accessed 19 May 2019].

Folgado, H., Duarte, R., Fernandes, O. and Sampaio, J., (2014) Competing with Lower Level Opponents Decreases Intra-Team Movement Synchronization and Time-Motion Demands during Pre-Season Soccer Matches. *PLoS ONE*, [online] 95. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4016249/ [Accessed 8 Apr. 2019].

Fradua, L., Zubillaga, A., Caro, O., Fernández-García, Á., Ruiz-Ruiz, C. and Tenga, A., (2012) Designing small-sided games for training tactical aspects in soccer: Extrapolating pitch sizes from full-size professional matches. *Journal of sports sciences*, 31.

Fredericson, M., Chew, K., Ngo, J., Cleek, T., Kiratli, J. and Cobb, K., (2007) Regional bone mineral density in male athletes: a comparison of soccer players, runners and controls. *British Journal of Sports Medicine*, 4110, pp.664–668.

García-Unanue, J., Pérez-Gómez, J., Giménez, J.-V., Felipe, J.L., Gómez-Pomares, S., Gallardo, L. and Sánchez-Sánchez, J., (2018) Influence of contextual variables and the pressure to keep category on physical match performance in soccer players. *PLoS ONE*, [online] 139. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6147482/ [Accessed 29 Apr. 2019].

Gaudino, P., Alberti, G. and Iaia, F.M., (2014) Estimated metabolic and mechanical demands during different small-sided games in elite soccer players. *Human Movement Science*, 36, pp.123–133.

Gaudino, P., Gaudino, C., Alberti, G. and Minetti, A.E., (2013) Biomechanics and predicted energetics of sprinting on sand: hints for soccer training. *Journal of Science and Medicine in Sport*, 163, pp.271–275.

Gaudino, P., Iaia, F.M., Alberti, G., Hawkins, R.D., Strudwick, A.J. and Gregson, W., (2014a) Systematic bias between running speed and metabolic power data in elite soccer players: influence of drill type. *International Journal of Sports Medicine*, 356, pp.489–493.

Gaudino, P., Iaia, F.M., Alberti, G., Strudwick, A.J., Atkinson, G. and Gregson, W., (2013a) Monitoring training in elite soccer players: systematic bias between running speed and metabolic power data. *International Journal of Sports Medicine*, 3411, pp.963–968.

Giovanelli, N., Louise Ryan Ortiz, A., Henninger, K. and Kram, R., (2015) Energetics of vertical kilometer foot races; Is steeper cheaper? *Journal of applied physiology (Bethesda, Md.: 1985)*, 120, pp.370–375.

Girard, O., Mendez-Villanueva, A. and Bishop, D., (2011) Repeated-sprint ability - part I: factors contributing to fatigue. *Sports Medicine (Auckland, N.Z.)*, 418, pp.673–694.

Girard, O. and Millet, G.P., (2009) Neuromuscular fatigue in racquet sports. *Physical Medicine and Rehabilitation Clinics of North America*, 201, pp.161–173, ix.

Goto, H. and King, J.A., (2019) High-Intensity Demands of 6-a-Side Small-Sided Games and 11-a-Side Matches in Youth Soccer Players. *Pediatric Exercise Science*, 311, pp.85–90.

Gray, A.J., Jenkins, D., Andrews, M.H., Taaffe, D.R. and Glover, M.L., (2010) Validity and reliability of GPS for measuring distance travelled in field-based team sports. *Journal of Sports Sciences*, 2812, pp.1319–1325.

Gregson, W., Drust, B., Atkinson, G. and Salvo, V.D., (2010) Match-to-match variability of high-speed activities in premier league soccer. *International Journal of Sports Medicine*, 314, pp.237–242.

Hader, K., Mendez-Villanueva, A., Palazzi, D., Ahmaidi, S. and Buchheit, M., (2016) Metabolic Power Requirement of Change of Direction Speed in Young Soccer Players: Not All Is What It Seems. *PLoS ONE (eCollection)*, 11, doi:10.1371/journal.pone.0149839.

Halvorsen, P., Sægrov, S., Mortensen, A., K. C. Kristensen, D., Eichhorn, A., Stenhaug, M., Dahl, S., Stensland, H., Gaddam, V., Griwodz, C. and Johansen, D., (2013) Bagadus: An integrated system for arena sports analytics - A soccer case study. Proceedings of the 4th ACM Multimedia Systems Conference, MMSys 2013. pp.48–59.

Harley, J.A., Lovell, R.J., Barnes, C.A., Portas, M.D. and Weston, M., (2011) The interchangeability of global positioning system and semiautomated video-based performance data during elite soccer match play. *Journal of Strength and Conditioning Research*, 258, pp.2334–2336.

Harrison, A.J., Jensen, R.L. and Donoghue, O., (2005) A Comparison of Laser and Video Techniques for Determining Displacement and Velocity During Running. *Measurement in Physical Education and Exercise Science*, 94, pp.219–231.

Haugen, T. and Buchheit, M., (2016) Sprint Running Performance Monitoring: Methodological and Practical Considerations. *Sports Medicine (Auckland, N.Z.)*, 465, pp.641–656.

Haugen, T., Tønnessen, E., Hisdal, J. and Seiler, S., (2014) The role and development of sprinting speed in soccer. *International Journal of Sports Physiology and Performance*, 93, pp.432–441.

Helgerud, J., Engen, L.C., Wisloff, U. and Hoff, J., (2001) Aerobic endurance training improves soccer performance. *Medicine and Science in Sports and Exercise*, 3311, pp.1925–1931.

Highton, J., Mullen, T., Norris, J., Oxendale, C. and Twist, C., (2017) The Unsuitability of Energy Expenditure Derived From Microtechnology for Assessing Internal Load in Collision-Based Activities. *International Journal of Sports Physiology and Performance*, 122, pp.264–267.

Hill-Haas, S.V., Dawson, B., Impellizzeri, F.M. and Coutts, A.J., (2011) Physiology of small-sided games training in soccer: a systematic review. *Sports Medicine (Auckland, N.Z.)*, 413, pp.199–220.

Hopkins, W.G., (2010) *A Socratic Dialogue on Comparison of Measures*. [online] Available at: https://www.sportsci.org/2010/wghmeasures.htm [Accessed 25 Apr. 2019].

Hopkins, W.G., (2002) *A Scale of Magnitudes for Effect Statistics. A New View of Statistics.* [online] Available at: http://www.sportsci.org/resource/stats/effectmag.html [Accessed 30 Sep. 2019].

Hopkins, W.G., (2004) *Bias in Bland-Altman but not Regression Validity Analyses*. [online] Available at: http://sportsci.org/jour/04/wghbias.htm [Accessed 25 Apr. 2019].

Hoppe, M.W., Baumgart, C., Slomka, M., Polglaze, T. and Freiwald, J., (2017) Variability of Metabolic Power Data in Elite Soccer Players During Pre-Season Matches. *Journal of Human Kinetics*, 58, pp.233–245.

Hoppe, M.W., Baumgart, C., Polglaze, T. and Freiwald, J., (2018) Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical

properties in team sports. *PLoS ONE*, 132,
https://doi.org/10.1371/journal.pone.0192708.

Hoppe, M.W., Slomka, M., Baumgart, C., Weber, H. and Freiwald, J., (2015) Match Running Performance and Success Across a Season in German Bundesliga Soccer Teams. *International Journal of Sports Medicine*, 367, pp.563–566.

Hughes, M.G., Birdsey, L., Meyers, R., Newcombe, D., Oliver, J.L., Smith, P.M., Stembridge, M., Stone, K. and Kerwin, D.G., (2013) Effects of playing surface on physiological responses and performance variables in a controlled soccer simulation. *Journal of Sports Sciences*, 318, pp.878–886.

Iaia, F.M., Rampinini, E. and Bangsbo, J., (2009) High-intensity training in soccer. *International Journal of Sports Physiology and Performance*, 43, pp.291–306.

Impellizzeri, F.M., Marcora, S.M., Castagna, C., Reilly, T., Sassi, A., Iaia, F.M. and Rampinini, E., (2006) Physiological and performance effects of generic versus specific aerobic training in soccer players. *International Journal of Sports Medicine*, 276, pp.483–492.

Impellizzeri, F.M., Rampinini, E., Coutts, A.J., Sassi, A. and Marcora, S.M., (2004) Use of RPE-based training load in soccer. *Medicine and Science in Sports and Exercise*, 366, pp.1042–1047.

Impellizzeri, F.M., Rampinini, E., Maffiuletti, N.A., Castagna, C., Bizzini, M. and Wisløff, U., (2008) Effects of aerobic training on the exercise-induced decline in short-passing ability in junior soccer players. *Applied Physiology, Nutrition, and Metabolism = Physiologie Appliquee, Nutrition Et Metabolisme*, 33, pp.1192–1198.

Impellizzeri, F.M., Rampinini, E. and Marcora, S.M., (2005) Physiological assessment of aerobic training in soccer. *Journal of Sports Sciences*, 236, pp.583–592.

Ingebrigtsen, J., Bendiksen, M., Randers, M.B., Castagna, C., Krustrup, P. and Holtermann, A., (2012) Yo-Yo IR2 testing of elite and sub-elite soccer players: performance, heart rate response and correlations to other interval tests. *Journal of Sports Sciences*, 3013, pp.1337–1345.

Izzo, R. and Lo Castro, L., (2015) The study of acceleration and deceleration capacity decrease in repeated sprints in soccer. *International Journal of Physical Education, Sports and Health P-ISSN: 2394-1685*, 2, pp.80–89.

Johnston, R.J., Watsford, M., Kelly, S.J., Pine, M.J. and Spurrs, R.W., (2013) The Validity and reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *Journal of strength and conditioning research / National Strength & Conditioning Association*, 28, pp.1649–1655.

Johnston, R.J., Watsford, M.L., Pine, M.J., Spurrs, R.W., Murphy, A.J. and Pruyn, E.C., (2012) The validity and reliability of 5-Hz global positioning system units to measure team sport movement demands. *Journal of Strength and Conditioning Research*, 263, pp.758–765.

Jennings, D., Cormack, S., Coutts, A.J., Boyd, L. and Aughey, R.J., (2010) The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *International Journal of Sports Physiology and Performance*, 53, pp.328–341.

Jennings, D., Cormack, S., Coutts, A.J., Boyd, L.J. and Aughey, R.J., (2010a) Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology and Performance*, 54, pp.565–569.

Jones, A.M. and Vanhatalo, A., (2017) The ‘Critical Power’ Concept: Applications to Sports Performance with a Focus on Intermittent High-Intensity Exercise. *Sports Medicine (Auckland, N.z.)*, 47Suppl 1, pp.65–78.

Kalapotharakos, V.I., Ziogas, G. and Tokmakidis, S.P., (2011) Seasonal aerobic performance variations in elite soccer players. *Journal of Strength and Conditioning Research*, 256, pp.1502–1507.

Kannekens, R., Elferink-Gemser, M.T. and Visscher, C., (2011) Positioning and deciding: key factors for talent development in soccer. *Scandinavian Journal of Medicine & Science in Sports*, 216, pp.846–852.

Kao, S., Tu, Y., Chen, W., Weng, D.J. and Ji, S.Y., (2013) Factors affecting the estimation of GPS receiver instrumental biases. *Survey Review*, 45328, pp.59–67.

Kaplan, E. and Hegarty, C., (2005) *Understanding GPS: Principles and Applications*. Artech House.

Kempton, T., Sirotic, A.C., Rampinini, E. and Coutts, A.J., (2015) Metabolic power demands of rugby league match play. *International Journal of Sports Physiology and Performance*, 101, pp.23–28.

Kinear, P.R., Gray, L.D., (1995). SPSS for Windows Made Simple. London: Lawrence Ehbaum, pp.228.

Krustrup, P., Mohr, M., Steensberg, A., Bencke, J., Kjaer, M. and Bangsbo, J., (2006) Muscle and blood metabolites during a soccer game: implications for sprint performance. *Medicine and Science in Sports and Exercise*, 386, pp.1165–1174.

Kyprianou, E. and Farioli, F., (2018) Balancing physical and tactical load in soccer: a holistic approach. [online] EKSP Journal. Available at: http://www.eksportsperformance.com/ekspjournal [Accessed 20 May 2019].

Lago-Ballesteros, J., Lago-Peñas, C. and Rey, E., (2012) The effect of playing tactics and situational variables on achieving score-box possessions in a professional soccer team. *Journal of Sports Sciences*, 3014, pp.1455–1461.

Lago-Peñas, C., (2012) The Role of Situational Variables in Analysing Physical Performance in Soccer. *Journal of Human Kinetics*, 35, pp.89–95.

Lamonte, M.J. and Ainsworth, B.E., (2001) Quantifying energy expenditure and physical activity in the context of dose response. *Medicine and Science in Sports and Exercise*, 33 (6 Suppl), pp.S370-378; discussion pp.S419-420.

Laursen, P.B. and Jenkins, D.G., (2002) The scientific basis for high-intensity interval training: optimising training programmes and maximising performance in highly trained endurance athletes. *Sports Medicine (Auckland, N.Z.)*, 321, pp.53–73.

Léger, L.A. and Lambert, J., (1982) A maximal multistage 20-m shuttle run test to predict VO2 max. *European Journal of Applied Physiology and Occupational Physiology*, 491, pp.1–12.

Linke, D., Link, D. and Lames, M., (2018) Validation of electronic performance and tracking systems EPTS under field conditions. *PLoS ONE (eCollection)*, 13, doi:10.1371/journal.pone.0199519.

Little, T., (2009) Optimizing the Use of Soccer Drills for Physiological Development. *Strength & Conditioning Journal*, 313, p.67.

Lorenz, D.S., Reiman, M.P., Lehecka, B.J. and Naylor, A., (2013) What Performance Characteristics Determine Elite Versus Nonelite Athletes in the Same Sport? *Sports Health*, 56, pp.542–547.

Ludbrook, J., (1997) Comparing methods of measurements. *Clinical and Experimental Pharmacology & Physiology*, 242, pp.193–203.

Ludbrook, J., (2002) Statistical techniques for comparing measurers and methods of measurement: a critical review. *Clinical and Experimental Pharmacology & Physiology*, 297, pp.527–536.

Ludbrook, J., (2010) Confidence in Altman-Bland plots: a critical review of the method of differences. *Clinical and Experimental Pharmacology & Physiology*, 372, pp.143–149.

Ludbrook, J., (2010a) Linear regression analysis for comparing two measurers or methods of measurement: but which regression? *Clinical and Experimental Pharmacology & Physiology*, 377, pp.692–699.

Ludbrook, J., (2012) A primer for biomedical scientists on how to execute Model II linear regression analysis. *Clinical and Experimental Pharmacology and Physiology,* 394, pp.329–335.

Maddison, R. and Ni Mhurchu, C., (2009) Global positioning system: a new opportunity in physical activity measurement. *The International Journal of Behavioral Nutrition and Physical Activity*, 6, p.73.

Mackenzie, R. and Cushion, C., (2013) Performance analysis in soccer: a critical review and implications for future research. *Journal of Sports Sciences*, 316, pp.639–676.

MacLeod, H., Morris, J., Nevill, A. and Sunderland, C., (2009) The validity of a non-differential global positioning system for assessing player movement patterns in field hockey. *Journal of Sports Sciences*, 272, pp.121–128.

Malone, J.J., Lovell, R., Varley, M.C. and Coutts, A.J., (2017) Unpacking the Black Box: Applications and Considerations for Using GPS Devices in Sport. *International Journal of Sports Physiology and Performance*, 12Suppl 2, pp.S218–S226.

Manzi, V., Impellizzeri, F. and Castagna, C., (2014) Aerobic fitness ecological validity in elite soccer players: a metabolic power approach. *Journal of Strength and Conditioning Research*, 284, pp.914–919.

Margaria, R., (1938) Sulla fisiologia e specialmente sul consumo energetico della marcia e della corsa a varie velocità ed inclinazioni del terreno. *Atti Accademia Nazionale dei Lincei*, 7, pp. 299–368.

Margaria, R., Cerretelli, P., Aghemo, P. and Sassi, G., (1963) Energy cost of running. *Journal of Applied Physiology*, 182, pp.367–370.

Martínez-Cabrera, F.I. and Núñez-Sánchez, F.J., (2018) The use of metabolic power to assess physical demands in soccer: how does it differ from the traditional approach through speed running? *The Journal of Sports Medicine and Physical Fitness*, 5810, pp.1403–1411.

Martín-García, A., Gómez Díaz, A., Bradley, P.S., Morera, F. and Casamichana, D., (2018) Quantification of a Professional Soccer Team's External Load Using a Microcycle Structure. *Journal of Strength and Conditioning Research*, 3212, pp.3511–3518.

McArdle, W.D., Katch, F.I. and Katch, V.L., (2006) *Essentials of Exercise Physiology*. Lippincott Williams & Wilkins.

McMillan, K., Helgerud, J., Macdonald, R. and Hoff, J., (2005) Physiological adaptations to soccer specific endurance training in professional youth soccer players. *British Journal of Sports Medicine*, 395, pp.273–277.

Minetti, A.E., Ardigò, L.P. and Saibene, F., (1994) Mechanical determinants of the minimum energy cost of gradient running in humans. *The Journal of Experimental Biology*, 195, pp.211–225.

Minetti, A.E., Gaudino, P., Seminati, E. and Cazzola, D., (2013) The cost of transport of human running is not affected, as in walking, by wide acceleration/deceleration cycles. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, 1144, pp.498–503.

Minetti, A.E., Moia, C., Roi, G.S., Susta, D. and Ferretti, G., (2002) Energy cost of walking and running at extreme uphill and downhill slopes. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, 933, pp.1039–1046.

Minetti, A.E. and Pavei, G., (2018) Update and extension of the ‘equivalent slope’ of speed-changing level locomotion in humans: a computational model for shuttle running. *The Journal of Experimental Biology*, 221(Pt 15), doi:10.1242/jeb.182303.

Mohr, M., Krustrup, P. and Bangsbo, J., (2003) Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of Sports Sciences*, 217, pp.519–528.

Mohr, M., Krustrup, P. and Bangsbo, J., (2005) Fatigue in soccer: A brief review. *Journal of sports sciences*, 23, pp.593–9.

Moreira, A., Saldanha Aoki, M., Carling, C., Alan Rodrigues Lopes, R., Felipe Schultz de Arruda, A., Lima, M., Cesar Correa, U. and Bradley, P.S., (2016) Temporal Changes in Technical and Physical Performances During a Small-Sided Game in Elite Youth

Soccer Players. *Asian Journal of Sports Medicine*, [online] 74. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5259671/ [Accessed 29 May 2019].

Nakamura, F.Y., Pereira, L.A., Loturco, I., Rosseti, M., Moura, F.A. and Bradley, P.S., (2017) Repeated-Sprint Sequences During Female Soccer Matches Using Fixed and Individual Speed Thresholds. *Journal of Strength and Conditioning Research*, 317, pp.1802–1810.

O'Donoghue, P.G., (2002) Time-motion analysis of work-rate in English FA Premier League soccer. *International Journal of Performance Analysis in Sport*, 21, pp.36–43.

Ogris, G., Leser, R., Horsak, B., Kornfeind, P., Heller, M. and Baca, A., (2012) Accuracy of the LPM tracking system considering dynamic position changes. *Journal of Sports Sciences*, 3014, pp.1503–1511.

Olthof, S.B.H., Frencken, W.G.P. and Lemmink, K.A.P.M., (2018) Match-derived relative pitch area changes the physical and team tactical performance of elite soccer players in small-sided soccer games. *Journal of Sports Sciences*, 3614, pp.1557–1563.

Osgnach, C., Paolini, E., Roberti, V., Vettor, M. and di Prampero, P.E., (2016) Metabolic Power and Oxygen Consumption in Team Sports: A Brief Response to Buchheit *et al*. *International Journal of Sports Medicine*, 371, pp.77–81.

Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R. and di Prampero, P.E., (2010) Energy cost and metabolic power in elite soccer: a new match analysis approach. *Medicine and Science in Sports and Exercise*, 421, pp.170–178.

Osgnach, C. and di Prampero, P.E., (2018) Metabolic Power in Team Sports - Part 2: Aerobic and Anaerobic Energy Yields. *International Journal of Sports Medicine*, 398, pp.588–595.

Oxendale, C.L., Highton, J. and Twist, C., (2017) Energy expenditure, metabolic power and high speed activity during linear and multi-directional running. *Journal of Science and Medicine in Sport*, 2010, pp.957–961.

Padulo, J., Iuliano, E., Brisola, G., Iacono, A.D., Zagatto, A.M., Lupo, C., Fuglsang, T., Ardigò, L.P. and Cular, D., (2019) Validity and reliability of a standalone low-end 50-Hz GNSS receiver during running. *Biology of Sport*, 361, pp.75–80.

Paradisis, G.P., Zacharogiannis, E., Mandila, D., Smirtiotou, A., Argeitaki, P. and Cooke, C.B., (2014) Multi-Stage 20-m Shuttle Run Fitness Test, Maximal Oxygen Uptake and Velocity at Maximal Oxygen Uptake. *Journal of Human Kinetics*, 41, pp.81–87.

Paul, D.J., Bradley, P.S. and Nassis, G.P., (2015) Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *International Journal of Sports Physiology and Performance*, 104, pp.516–519.

Petersen, C., Pyne, D., Portus, M. and Dawson, B., (2009) Validity and reliability of GPS units to monitor cricket-specific movement patterns. *International Journal of Sports Physiology and Performance*, 43, pp.381–393.

Pinnington, H.C. and Dawson, B., (2001) The energy cost of running on grass compared to soft dry beach sand. *Journal of Science and Medicine in Sport*, 44, pp.416–430.

Polglaze, T., (2017) *Metabolic power in team sports – controversies*. 22nd Annual Congress of the European College of Sport Science 2017; Pre-conference workshop, Essen, Germany.

Polglaze, T., Dawson, B., Buttfield, A. and Peeling, P., (2018) Metabolic power and energy expenditure in an international men's hockey tournament. *Journal of Sports Sciences*, 362, pp.140–148.

Polglaze, T., Dawson, B. and Peeling, P., (2016) Gold Standard or Fool's Gold? The Efficacy of Displacement Variables as Indicators of Energy Expenditure in Team Sports. *Sports Medicine (Auckland, N.Z.)*, 465, pp.657–670.

Polglaze, T., Hogan, C., Dawson, B., Buttfield, A., Osgnach, C., Lester, L. and Peeling, P., (2018a) Classification of Intensity in Team Sport Activity. *Medicine and Science in Sports and Exercise*, 507, pp.1487–1494.

Polglaze, T. and Hoppe, M.W., (2019) Metabolic Power: A Step in the Right Direction for Team Sports. *International Journal of Sports Physiology and Performance*, 143, pp.407–411.

Pons, E., García-Calvo, T., Resta, R., Blanco, H., López del Campo, R., Díaz García, J. and Pulido, J.J., (2019) A comparison of a GPS device and a multi-camera video technology during official soccer matches: Agreement between systems. *PLoS ONE*, [online] 148. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6687125/ [Accessed 9 Dec. 2019].

Portas, M.D., Harley, J.A., Barnes, C.A. and Rush, C.J., (2010) The validity and reliability of 1-Hz and 5-Hz global positioning systems for linear, multidirectional, and soccer-specific activities. *International Journal of Sports Physiology and Performance*, 54, pp.448–458.

Pullinger, S., Bradley, P., Causer, J., Ford, P., Patel, K., Reid, K., Newlove, A., Robertson, C., Burniston, J., Doran, D., M. Waterhouse, J. and Edwards, B., (2019) Soccer-induced fatigue in hypoxia impairs repeated sprint ability and perceptual-cognitive skills. *Science and Medicine in Soccer*, doi:10.1080/24733938.2019.1591633

Rampinini, E., Alberti, G., Fiorenza, M., Riggio, M., Sassi, R., Borges, T.O. and Coutts, A.J., (2015) Accuracy of GPS devices for measuring high-intensity running in field-based team sports. *International Journal of Sports Medicine*, 361, pp.49–53.

Rampinini, E., Impellizzeri, F.M., Castagna, C., Coutts, A.J. and Wisløff, U., (2009) Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. *Journal of Science and Medicine in Sport*, 121, pp.227–233.

Randers, M.B., Mujika, I., Hewitt, A., Santisteban, J., Bischoff, R., Solano, R., Zubillaga, A., Peltola, E., Krustrup, P. and Mohr, M., (2010) Application of four different soccer match analysis systems: a comparative study. *Journal of Sports Sciences*, 282, pp.171–182.

Reilly, T., (1997) Energetics of high-intensity exercise (soccer) with particular reference to fatigue. *Journal of Sports Sciences*, 153, pp.257–263.

Reilly, T., Bangsbo, J. and Franks, A., (2000) Anthropometric and physiological predispositions for elite soccer. *Journal of Sports Sciences*, 189, pp.669–683.

Reilly, T. and Williams, A.M., (2003) *Science and Soccer*. Psychology Press.

Rein, R. and Memmert, D., (2016) Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus*, 51, p.1410.

Rodio, A., Fattorini, L., Scarcia, M., Stropiccioli, A. and Ballesio, M., (2004) Energy demand of running on soccer field in synthetic or natural grass. *Medicina dello Sport*, 57, pp.109–114.

Roe, G., Darrall-Jones, J., Black, C., Shaw, W., Till, K. and Jones, B., (2017) Validity of 10-HZ GPS and Timing Gates for Assessing Maximum Velocity in Professional Rugby Union Players. *International Journal of Sports Physiology and Performance*, 126, pp.836–839.

Rogalski, B., Dawson, B., Heasman, J. and Gabbett, T.J., (2013) Training and game loads and injury risk in elite Australian footballers. *Journal of Science and Medicine in Sport*, 166, pp.499–503.

Sampaio, J. and Maçãs, V., (2012) Measuring tactical behaviour in soccer. *International Journal of Sports Medicine*, 335, pp.395–401.

Santos-Silva, P.R., Pedrinelli, A., Greve, J.M.D., Santos-Silva, P.R., Pedrinelli, A. and Greve, J.M.D., (2017) Blood lactate and oxygen consumption in soccer players: comparison between different positions on the field. *MedicalExpress*, [online] 41. Available at: http://www.scielo.br/scielo.php?script=sci_abstract&pid=S2358-04292017000100002&lng=en&nrm=iso&tlng=en [Accessed 29 Jul. 2019].

Sangnier, S., Cotte, T., Brachet, O., Coquart, J. and Tourny, C., (2018) Planning Training Workload in Soccer Using Small-Sided Games' Density. *Journal of Strength and Conditioning Research*. Advance online publication. doi:10.1519/JSC.0000000000002598

Sarmento, H., Marcelino, R., Anguera, M.T., Campaniço, J., Matos, N. and Leitão, J.C., (2014) Match analysis in soccer: a systematic review. *Journal of Sports Sciences*, 3220, pp.1831–1843.

Sassi, A., Stefanescu, A., Menaspà, P., Bosio, A., Riggio, M. and Rampinini, E., (2011) The cost of running on natural grass and artificial turf surfaces. *Journal of Strength and Conditioning Research*, 253, pp.606–611.

Schimpchen, J., Skorski, S., Nopp, S. and Meyer, T., (2016) Are ‘classical’ tests of repeated-sprint ability in soccer externally valid? A new approach to determine in-game sprinting behaviour in elite soccer players. *Journal of Sports Sciences,* 346, pp.519–526.

Schutz, Y. and Chambaz, A., (1997) Could a satellite-based navigation system (GPS) be used to assess the physical activity of individuals on earth? *European Journal of Clinical Nutrition*, 515, pp.338–339.

Sloth, M., Sloth, D., Overgaard, K. and Dalgas, U., (2013) Effects of sprint interval training on VO2max and aerobic exercise performance: A systematic review and meta-analysis. *Scandinavian Journal of Medicine & Science in Sports*, 236, pp.e341-352.

Sonderegger, K., Tschopp, M. and Taube, W., (2016) The Challenge of Evaluating the Intensity of Short Actions in Soccer: A New Methodological Approach Using Percentage Acceleration. *PLoS ONE (eCollection*), 11, doi:10.1371/journal.pone.0166534.

Steede-Terry, K., (2000) *Integrating GIS and the Global Positioning System*. Redlands, California: ESRI Press.

Stevens T, G.A., de Ruiter, C.J., van Niel, C., van de Rhee, R., Beek, P.J. and Savelsbergh, G.J.P., (2014) Measuring acceleration and deceleration in soccer-specific movements using a local position measurement (LPM) system. *International Journal of Sports Physiology and Performance*, 93, pp.446–456.

Stevens, T.G.A., De Ruiter, C.J., Van Maurik, D., Van Lierop, C.J.W., Savelsbergh, G.J.P. and Beek, P.J., (2015) Measured and estimated energy cost of constant and shuttle running in soccer players. *Medicine and Science in Sports and Exercise*, 476, pp.1219–1224.

Stølen, T., Chamari, K., Castagna, C. and Wisløff, U., (2005) Physiology of soccer: an update. *Sports Medicine (Auckland, N.Z.)*, 356, pp.501–536.

Svensson, M. and Drust, B., (2005) Testing soccer players. *Journal of Sports Sciences*, 236, pp.601–618.

Taberner, M., O’Keefe, J., Flower, D., Phillips, J., Close, G., Cohen, D.D., Richter, C. and Carling, C., (2019) Interchangeability of position tracking technologies; can we merge the data? *Science and Medicine in Football*, 00, pp.1–6.

Tang, R., Murtagh, C., Warrington, G., Cable, T., Morgan, O., O’Boyle, A., Burgess, D., Morgans, R. and Drust, B., (2018) Directional Change Mediates the Physiological Response to High-Intensity Shuttle Running in Professional Soccer Players. *Sports*, [online] 62. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6026794/ [Accessed 29 Jul. 2019].

Taylor, J.B., Wright, A.A., Dischiavi, S.L., Townsend, M.A. and Marmon, A.R., (2017) Activity Demands During Multi-Directional Team Sports: A Systematic Review. *Sports Medicine (Auckland, N.Z.)*, 4712, pp.2533–2551.

Terrier, P., Turner, V. and Schutz, Y., (2005) GPS analysis of human locomotion: further evidence for long-range correlations in stride-to-stride fluctuations of gait parameters. *Human Movement Science*, 241, pp.97–115.

Thornton, H.R., Delaney, J.A., Duthie, G.M. and Dascombe, B.J., (2017) Importance of Various Training-Load Measures in Injury Incidence of Professional Rugby League Athletes. *International Journal of Sports Physiology and Performance*, 126, pp.819–824.

Thorpe, R.T., Strudwick, A.J., Buchheit, M., Atkinson, G., Drust, B. and Gregson, W., (2015) Monitoring Fatigue During the In-Season Competitive Phase in Elite Soccer

Players. *International Journal of Sports Physiology and Performance*, 108, pp.958–964.

Tierney, P.J., Young, A., Clarke, N.D. and Duncan, M.J., (2016) Match play demands of 11 versus 11 professional football using Global Positioning System tracking: Variations across common playing formations. *Human Movement Science*, 49, pp.1–8.

Varley, M.C. and Aughey, R.J., (2013) Acceleration profiles in elite Australian soccer. *International Journal of Sports Medicine*, 341, pp.34–39.

Varley, M.C., Fairweather, I.H. and Aughey, R.J., (2012) Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *Journal of Sports Sciences*, 302, pp.121–127.

Varley, M.C., Gabbett, T. and Aughey, R.J., (2014) Activity profiles of professional soccer, rugby league and Australian soccer match play. *Journal of Sports Sciences*, 3220, pp.1858–1866.

Varley, M.C., Jaspers, A., Helsen, W.F. and Malone, J.J., (2017) Methodological Considerations When Quantifying High-Intensity Efforts in Team Sport Using Global Positioning System Technology. *International Journal of Sports Physiology and Performance*, 128, pp.1059–1068.

Vescovi, J.D. and Favero, T.G., (2014) Motion characteristics of women's college soccer matches: Female Athletes in Motion (FAiM) study. *International Journal of Sports Physiology and Performance*, 93, pp.405–414.

Vickery, W.M., Dascombe, B.J., Baker, J.D., Higham, D.G., Spratford, W.A. and Duffield, R., (2014) Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. *Journal of Strength and Conditioning Research*, 286, pp.1697–1705.

Vigne, G., Gaudino, C., Rogowski, I., Alloatti, G. and Hautier, C., (2010) Activity profile in elite Italian soccer team. *International Journal of Sports Medicine*, 315, pp.304–310.

Waldron, M., Worsfold, P., Twist, C. and Lamb, K., (2011) Concurrent validity and test-retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables. *Journal of Sports Sciences*, 2915, pp.1613–1619.

Walker, E.J., McAinch, A.J., Sweeting, A. and Aughey, R.J., (2016) Inertial sensors to estimate the energy expenditure of team-sport athletes. *Journal of Science and Medicine in Sport*, 192, pp.177–181.

Wallace, J.L. and Norton, K.I., (2014) Evolution of World Cup soccer final games 1966–2010: Game structure, speed and play patterns. *Journal of Science and Medicine in Sport*, 172, pp.223–228.

Ward-Smith, A.J. and Radford, P.F., (2000) Investigation of the kinetics of anaerobic metabolism by analysis of the performance of elite sprinters. *Journal of Biomechanics*, 338, pp.997–1004.

Whitehead, S., Till, K., Weaving, D. and Jones, B., (2018) The Use of Microtechnology to Quantify the Peak Match Demands of the Soccer Codes: A Systematic Review. *Sports Medicine (Auckland, N.Z.)*, 4811, pp.2549–2575.

Williams, M. and Morgan, S., (2009) Horizontal positioning error derived from stationary GPS units: A function of time and proximity to building infrastructure. *International Journal of Performance Analysis in Sport*, 92, pp.275–280.

Witte, T.H. and Wilson, A.M., (2004) Accuracy of non-differential GPS for the determination of speed over ground. *Journal of Biomechanics*, 3712, pp.1891–1898.

Wong, P.-L., Chaouachi, A., Castagna, C., Lau, P.W.C., Chamari, K. and Wisløff, U., (2011) Validity of the Yo-Yo intermittent endurance test in young soccer players. *European Journal of Sport Science*, 115, pp.309–315.

Yanci, J., Calleja-Gonzalez, J., Cámara, J., Mejuto, G., San Román, J. and Los Arcos, A., (2017) Validity and reliability of a global positioning system to assess 20 m sprint performance in soccer players. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, 2311, pp.68–71.

Zadro, I., Sepulcri, L., Lazzer, S., Fregolent, R. and Zamparo, P., (2011) A protocol of intermittent exercise (shuttle runs) to train young basketball players. *Journal of Strength and Conditioning Research*, 256, pp.1767–1773.

Appendix

Thank you very much for your academic support rendered through workshops, conferences, research projects, writing retreats.

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TO WHOM IT MAY CONCERN

I read with great interest the enclosed project proposal the aim of which it to redefine in clear physiological terms match and training characteristics in soccer.

The traditional approach for the assessment of physical performances of professional soccer players by means of video match analysis is based on the identification of time and distance covered at “high intensities” considered as “high running speeds”. However, even at low speed, any eventual acceleration phases, because of the resulting increase of kinetic energy lead to an extra metabolic load. Hence, both running speed and acceleration must be taken into account to estimate the overall metabolic power.

In 2005 P.E. di Prampero et al. showed that accelerated running on a flat terrain is equivalent to running uphill at constant speed, the incline being dictated by the forward acceleration. Since the energy cost of running uphill (per unit body mass and distance) is known, this makes it possible to estimate the instantaneous energy cost of accelerated running, the corresponding metabolic power, and the overall energy expenditure, provided that speed, acceleration and distance covered are known.

Therefore, video match analysis data from 399 Italian ‘‘Serie-A’’ soccer players, collected during the 2007–2008, season were processed in accordance with the approach described above (C. Osgnach et al., 2010). The results show that the ‘‘high intensities’’, expressed as high-power outputs (estimated as describe above), are two to three times larger than those based only on running speed alone, thus suggesting that further studies along these lines are highly desirable.

The approach summarised in the enclosed project proposal, based as it is on GPS analysis of speed and acceleration and on actual comparison of estimated and measured energy costs of accelerated running is a substantial advance toward a more accurate definition of ‘‘high intensity’’ based on actual metabolic power, rather than on speed alone. In addition, making the whole approach much more “user friendly”, the results obtained will allow to better understand the differences among players and roles, in order to propose a customized training load.

In conclusion I hereby suggest that the proposed study be appropriately supported.

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