



**UiT** The Arctic University of Norway

Faculty of Health Sciences - School of Sport Sciences

## **Football training specificity**

Training individualization within the collective periodization

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## Abstract

Some limitations and arguments have been raised in the literature about the validity, reliability and usefulness of tracking system technologies, such as global positioning systems (GPS), video tracking performed manually to automatically and local radio positioning systems (LPM). The questionable validity of data acquisition of some systems can be detected when comparing data from multiple systems and thus the aim of Paper 1 was to highlight some of the challenges encountered when using positional data as part of the research and team development, and to recommend other possible data sources. This Paper was divided into two studies: (a) in study 1, the Copenhagen Soccer Test for Women was performed by six high-level female players using both GPS and LPM tags; (b) in study 2, 12 male youth elite players were instructed to jog around the pitch, while simultaneously wearing both GPS and ZXY system. In the intra reliability test in study 1, the measured discrepancy between the two tags placed on the same player ranges between 800-2071 m using StatSport SPI-ProX1 and 25-290 m using ZXY system. In study 2, the sprint performance was measured lower by ZXY system ( $55.3 \pm 7.3$  m) compared to Polar Team Pro ( $70 \pm 12.9$  m) ( $p > 0.05$ ). High-intensity runs (HIR) and number of accelerations ( $acc_{counts}$ ) showed an inverse tendency with higher values:  $222.8 \pm 77.8$  m and  $100.9 \pm 19.9$  counts vs.  $164.4 \pm 54.9$  m and  $81.0 \pm 15.9$  counts.

The majority of research supports the idea that different playing positions present different external load profiles in match-play and that the large individual variation in activity patterns is, among other things, associated with playing position. Therefore, the aims of Paper 2 were to quantify and compare the physical demands during official matches across playing positions, with special emphasis on accelerations ( $acc$ ), decelerations ( $dec$ ), turns and lengths of HIR and sprints. Performance data from 23 official home matches, including 18 elite players divided into five different playing positions, was collected for analysis. Regarding  $HIR_{dist}$ , centre forwards (CF) presented higher values in 26-30 m ( $4.3 \pm 1.2$ ) than all the other positions, while distances of 36-40 and 46-50 m were covered more times by full-backs (FB) ( $1.7 \pm 1.4$ ;  $0.9 \pm 1.0$ ). Distances of 1-5 m in HIR were the distances covered more often by all the playing positions, with exception of FB who had higher values in distances of 6-10 m. Furthermore, a pattern of covariance in the work-rates analysed was observed across playing positions.

The simple report of distances and frequency of occurrence, without trying to establish connections with other important performance domains, such as the tactical aspects, leads researchers to a lack of insights provided to coaches. Consequently, a deeper analysis of match performance across playing positions in different tactical formations, could provide useful

insight to optimize training programs, team periodization and tactical changes. Thus, the aim of Paper 3 was to analyse how different tactical systems affect the physical performance in match-play of a professional football team. Data on performance from 15 official matches, from 22 elite players, playing in two different tactical formations (1-4-5-1 vs 1-3-5-2), was collected for analysis. The players were divided into four different playing positions and a total of 139 match observations ( $M_{\text{obs}}$ ) were used. CF and wide positions did not present any significant difference between the tactical formations analysed. However, significant differences were found in various parameters when comparing the physical performance of the whole team in the two different formations. Significant higher values were observed in the number of HIR ( $\text{HIR}_{\text{counts}}$ ) ( $r = 0.25$ ) and number of sprints ( $\text{sprint}_{\text{counts}}$ ) ( $r = 0.22$ ) when playing in 1-4-5-1 ( $43.6 \pm 1.9$ ;  $11.4 \pm 1.1$ ) compared with 1-3-5-2 ( $40.0 \pm 2.0$ ;  $10.0 \pm 1.1$ ) ( $p=0.005$ ;  $p=0.0015$ ).

Most existing technology in football relies on post-game/training analysis, however, its weakness is the lack of instant feedback during matches and trainings. Therefore, in Paper 4 we developed Metrix: a computerized toolkit for coaches to perform real-time monitoring and analysis of the players' performance.

In contrast to detailed information regarding matches, few studies have focused on the training practices of elite football clubs. This information might be useful when prescribing training programs and to gain insight into the relative load of training compared to matches. Thus, the aims of Paper 5 were to quantify and compare: a) the most demanding passages of play in training sessions and matches; b) and the accumulated load of microcycles and official matches, by playing position. Players performance data (18 outfield players) from 15 official home matches and 11 in-season microcycles was collected for analysis. Players were divided into four different playing positions: centre backs (CB) ( $n=4$ ;  $M_{\text{obs}}=42$ ; training observations ( $T_{\text{obs}}=141$ ), wing-backs (WB) ( $n=3$ ;  $M_{\text{obs}}=21$ ;  $T_{\text{obs}}=101$ ), centre midfielders (CM) ( $n=5$ ;  $M_{\text{obs}}=40$ ;  $T_{\text{obs}}=162$ ) and CF ( $n=6$ ;  $M_{\text{obs}}=32$ ;  $T_{\text{obs}}=133$ ). Match demands were largely overperformed for  $\text{acc}_{\text{counts}}$  (131-166%) and number of decelerations ( $\text{dec}_{\text{counts}}$ ) (108-134%), by all the playing positions. However, relative to match values, training values for sprinting distance ( $\text{sprint}_{\text{dist}}$ ) and HIR distance ( $\text{HIR}_{\text{dist}}$ ) were considerably lower (36-61% and 57-71%) than for acc and dec. One of the most pronounced differences was observed between playing positions in 5-min peak of sprinting distance ( $\text{sprint}_{\text{peak}}$ ), with WB achieving, during the microcycle peaks, only 64% of the most demanding 5-min sprinting in matches, while CB, CM and CF levelled and overperformed the match values (107%, 100% and 107%, respectively). Moreover, we aim to illustrate how match performance data can be applied to daily practices in order to improve the specificity of training periodization.

## List of Papers

### *Paper 1:*

**Pettersen SA, Johansen HD, Baptista IAM, Halvorsen P and Johansen D** (2018). Quantified Soccer Using Positional Data: A Case Study. *Front. Physiol.* 9:866. <https://doi.org/10.3389/fphys.2018.00866>

### *Paper 2:*

**Baptista I, Johansen D, Seabra A, Pettersen SA** (2018). Position specific player load during match-play in a professional football club. *PLoS ONE* 13(5): e0198115. <https://doi.org/10.1371/journal.pone.0198115>

### *Paper 3:*

**Baptista I, Johansen D, Figueiredo P, Rebelo A, Pettersen SA** (2019). A comparison of match-physical demands between different tactical systems: 1-4-5-1 vs 1-3-5-2. *PLoS ONE* 14(4): e0214952. <https://doi.org/10.1371/journal.pone.0214952>

### *Paper 4:*

**Andreassen K, Johansen D, Johansen H, Baptista I, Pettersen SA, Riegler M, Halvorsen P** (2019). Real-time Analysis of Physical Performance Parameters in Elite Soccer. *Proceedings of the ACM International Workshop on Content-Based Multimedia Indexing (CBMI)*.

### *Paper 5:*

**Baptista I, Johansen D, Figueiredo P, Rebelo A, Pettersen SA** (2019). Positional differences on most demanding passages and accumulated training load relative to match load in elite football players. (*Under review*).

## Abbreviations

5-min peak of accelerations –  $acc_{peak}$

5-min peak of decelerations –  $dec_{peak}$

5-min peak of high-intensity runs distance –  $HIR_{peak}$

5-min peak of sprint distance -  $sprint_{peak}$

Accelerations –  $acc$

Acceleration distance per minute (work rate) –  $Acc_{wr}$

Centre backs – CB

Centre forwards – CF

Centre midfielders – CM

Decelerations –  $dec$

Deceleration distance -  $dec_{dist}$

Deceleration work rate –  $Dec_{wr}$

Full backs – FB

Global positioning systems – GPS

High-intensity runs – HIR

HIR distance –  $HIR_{dist}$

HIR work rate –  $HIR_{wr}$

Local positioning systems – LPM

Match load – ML

Match observations –  $M_{obs}$

Number of accelerations –  $Acc_{counts}$

Number of decelerations –  $Dec_{counts}$

Number of high-intensive runs –  $HIR_{counts}$

Number of sprints -  $sprint_{counts}$

Observations – Obs

Rated perceived exertion – RPE

Sprint distance –  $Sprint_{dist}$

Sprint work rate –  $Sprint_{wr}$

Training load – TL

Training observations –  $T_{obs}$

Wide midfielders – WM

Wing backs – WB

# 1 Introduction

## 1.1 Tracking technology

In the last decades, a technological revolution has been undergoing in sports and especially in the football environment, with the appearance of numerous wearable devices for quantification of external load. With this ongoing development of (micro) technology, the tracking of player's activity profile has become an essential part of load management in professional football clubs (1). The increasing availability and use of quantification of athlete's performance data through time-motion analysis alongside with tri-axial accelerometers have helped practitioners to extend the understanding of the metabolic, physiologic and mechanical load accumulated both in training and competition (2, 3). These data collection techniques, used by elite teams, have mostly been applied to quantify relative or absolute distances covered, as well as time spent within different speed zones (4).

Even though it is difficult to find an elite team not using any kind of tracking system, such as GPS, video-based systems or LPM, some limitations and arguments have been raised in the literature about the validity, reliability and usefulness of such devices (5). In fact, during a long period of time, tracking technology was used to collect only broad measures such as running distances at different speeds, while other important variables, such as acc and dec were neglected (1, 6). The shortcomings and questionable validity of data acquisition of some systems can be detected when combining data from multiple systems (7), and thus in Paper 1 a real-life comparison of some tracking systems was addressed.

When trying to measure training load (TL) and match load (ML) other limitations are raised by researchers, such as the fact that most of the elite teams use GPS during training sessions, while in competition video-based tracking systems are the most common choice (5). TL (the product of volume and intensity of training) can be divided in internal and external load (8, 9). The external load is often defined as the training process prescribed by the coaches, which means it refers to the output of physical activities performed by the athletes. The internal load, on the other hand, is presented as the physiological response to the external training load (9, 10). While external load was quantified through the daily use of tracking systems (e.g. LPM and GPS), subjective internal load and wellness status were assessed using a player monitoring system (PMSys), primarily developed at the computer science department of UiT The Arctic University of Norway (11). In Figure 1, we present the reporting process (five brief questions) of the rated perceived exertion (RPE) as well as one example of the data overview available for

coaches. In this project, even though both internal and external load were considered, in general external load is presented throughout the different Papers.

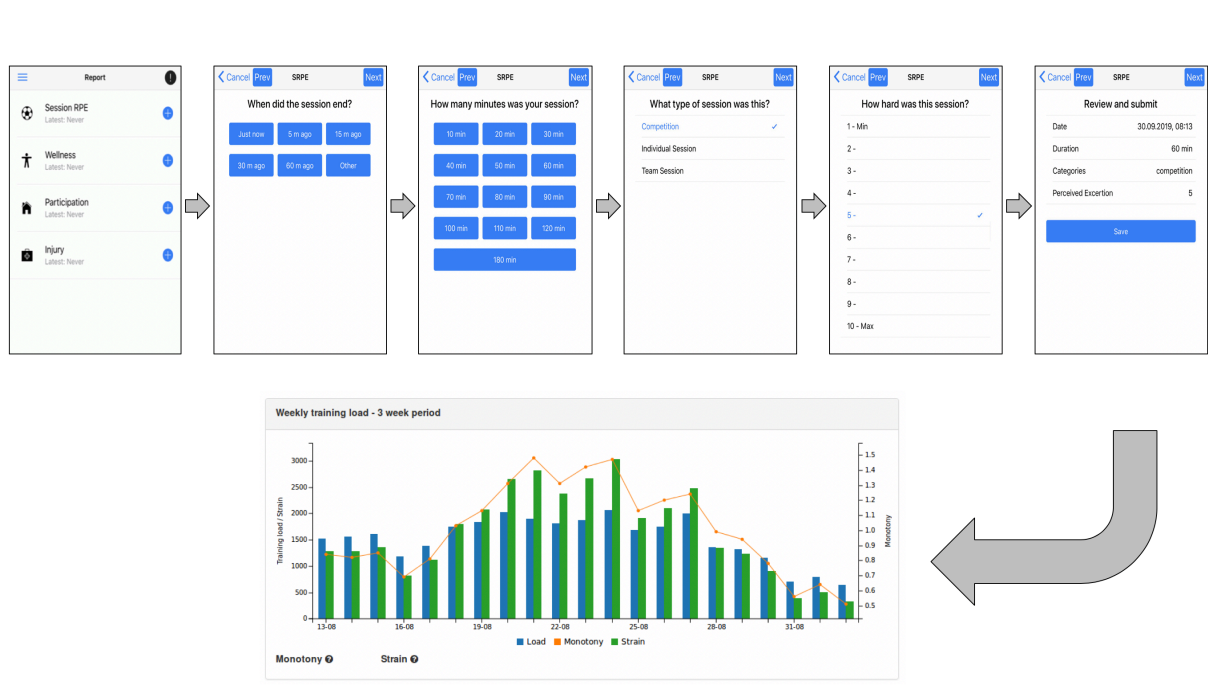


Figure 1. Player Monitoring System - RPE reporting process and data overview

In relation to external load quantification, previous studies (10, 12, 13) have shown that the accuracy of GPS and video-based systems when measuring high speed and (short) non-linear courses is somewhat doubtful. In order to minimize such limitations, in this project the trainings and matches were tracked using the same tracking system (LPM). LPM, as one of the recently introduced electronic systems, have been considered one of the most accurate among the tracking technologies available, particularly when measuring acc and dec using positional data (10, 14). Furthermore, considering that there are advantages and disadvantages in all the systems and that the variables provided are more or less the same, the most relevant decision to be taken by clubs and practitioners is to focus on the most useful variables available (5). Therefore, in our studies, we decided to give a special emphasis to variables less documented within the literature, but at the same time fundamental to better understand the physiological and mechanical load of players, such as acc, dec, turns, peaks of HIR and sprints, etc.

## 1.2 The complexity of football performance

Football is a complex sport of a high-intensive intermittent nature, where players have to perform complex and unpredictable movement patterns dictated by an array of variables (15-18). Football players may be required to repeat sprints, acc and turns of short duration, interspersed by bouts of low to moderate intensity movement (1, 17), and these activities are considered crucial factors for team performance (19-22). Researchers have been pointing HIR and sprints as the most important measurements for physical match performance (18, 23-25), because they are often used at critical moments such as contests for the ball, defensive or offensive actions and goal-scoring opportunities (26, 27). The contribution of HIR and sprints to the total distance travelled during official matches ranges from 3-11% (1, 27). Despite this, the use of only total distance and distance travelled in different speed zones may underestimate the calculation of players' external load, since this type of time-motion analysis neglects some critical and football-specific movements (acc, dec, turns, etc.) that together appear numerous times during every match and may cause significant physical stress on the players (23, 28). The ability of a player to perform movements at different speeds is known to influence the physical performance during matches (1), which means that performing high-intensity actions also requires the capacity to constantly accelerate and decelerate throughout match-play. However, these actions have rarely been measured during matches or trainings and its influence on player's physical performance remains poorly understood (28, 29).

Furthermore, the majority of research supports the idea that different playing positions present different external load profiles in match-play and that the large individual variation in activity patterns is, among other things, associated with playing position (17, 30-32). Consequently, we addressed special attention to *playing positions* in all the Papers included in this thesis.

During the last decades, one of the biggest challenges for researchers was to contextualize the physical data presented, following the idea that activity patterns of players are more contextual and tactical dependent (coaches' feed-back, rules, match score, etc.) than influenced by their fitness level (5). Moreover, the simple report of distances covered and frequency of occurrence of specific variables leads researchers to a lack of insight resulting in incomplete information provided to coaches and players (4, 33-35). Therefore, researchers should try to establish connections with other important performance domains, such the technical and/or tactical. This approach is supported by previous research which has focused on the influence of different factors in the player's match running profiles, such as the possession status (36,

37), seasonal fluctuations (17), competitive standard (38), opponent (39), playing positions (40, 41) and tactical systems (42). Even though, most of the research has been performed with a special emphasis on the technical and physical domain, some authors have started to find connections between tactical behaviour and physiological demands in professional football (24, 40, 43, 44). The team tactical formation and the positioning and distribution of the player on the pitch are considered among the most important strategical decisions in football (44, 45) and it is evident that the players external load is influenced by various factors, such as the tactical system used (42) and the playing position (40, 41). Indeed, it seems important for coaches and practitioners to take into consideration how physical match demands of different playing positions are affected by different tactical systems. However, there is still a lack of research and information within this field, and such problems can be observed in a systematic review (2012-2016) on match analysis in adult male football (46), where the tactical domain is not included in the contextual variables of research analysed (quality of opposition, scoring first, substitutions, match half, match location, competitive level, different competitions and group stage vs knockout phase). Despite some previous research (47, 48) have analysed the team positioning on the field, using the measures of centre and dispersion, the role of the tactical formation regarding the players' physical performance remains unclear. Consequently, a deeper analysis of match performance across playing positions, in different tactical formations, could provide a useful insight to optimize training programs, team periodization and tactical changes.

### **1.3 Match load and its relation to training**

The competition and training in other collective and individual sports have significantly evolved during the last years, with the advances in physical and/or tactical preparation being one of the reasons for such development (49-52). Football reality does not differ from the majority of the sports, and previous research shows that match demands and the players behaviour on-field have evolved too (4, 53). For instance, some authors (33, 53, 54), compared the evolution of English Premier League between the 2006/2007 and 2012/2013 seasons and presented differences in both physical and technical parameters across the whole team but also in particular playing positions. Changes in physical and technical performance during competition were also associated with tactical evolutions, more particularly with the use of different playing formations (53). This evolution in match demands as well as the marked positional differences previously shown in other studies (10, 28, 40, 55-57) require an equal



evolution and adaptation of training methods used by coaches and practitioners so players can be better prepared for competition.

In order to provide new insights into performance metrics, some technological advances have been made in the use of quantified data and associated analytics. Such advances may be used by coaches as a foundation for evidence-based decisions regarding team performances and improvements. However, nowadays with the use of automated or semi-automated tools, most of data quantification methods rely on post-game analytics. Even though posterior evaluation is useful and allows coaches to apply corrections to team's performance, its biggest weakness is the lack of immediate feedback while matches and practices are ongoing. Therefore, the immediate availability of such data is needed in order to allow coaches and sport scientists to make more informed decisions when trying to optimize the individual players' performance.

Football teams playing at elite level have to deal with small performance margins, and to do so TL should be managed carefully. Accordingly, monitoring and quantifying TL relative to ML may help coaches to improve the athlete's specific preparation for competition. While ML and the workload of small-sided games are well described in the literature (2, 16, 17, 38, 40, 46, 55, 56, 58-65), the available information regarding the weekly TL of elite football teams, in particular with respect to acc and peaks of HIR and sprints, is still scarce.

One major limitation in the majority of tracking and training load studies is the lack of application into practice (4, 66), which means that a more contextual-specific and practical-oriented approach is needed. With such an approach, and following the law of training specificity (67), practitioners may obtain new insights in order to better prepare their athletes for physical (and other) demands of competition.

## 2 Aims of the thesis

The overall aim of the thesis is to assess the different levels of specificity (similarity to match-play) that different playing-positions are subject to during training sessions in an elite football club. We hypothesize the following:

*Different playing positions accumulate different relative training load compared to their match demands.*

The specific research questions of the thesis are:

Paper 1) To highlight some of the challenges encountered when using positional data as part of the research and team development, and to recommend possible data sources.

Paper 2) To establish and compare the physical demands during official matches in five different playing positions, with special emphasis on acc, dec, turns and lengths of HIR and sprints.

Paper 3) To analyse how different tactical systems affect the physical performance of a professional football team across different playing positions in match-play.

Paper 4) To develop a real-time monitoring toolkit, in order to illustrate how match performance data can be applied to daily practices and to improve the specificity of training periodization.

Paper 5) To quantify and compare: a) the most demanding passages of play in training sessions and matches; b) and the accumulated load of typical training weeks (7 days-microcycles) and official matches, of the whole team and per playing position.

## **3 Materials and Methods**

### **3.1 Quantitative methods**

Scientific environment can benefit from the quantification of many physical, social and psychological variables, and therefore quantitative methods are required. In sport science, quantitative methods rather than qualitative have been widely used since data that can be measured and counted gain scientific credibility over the unmeasurable (68). For the purpose of this thesis we only used quantitative methods to analyse the players' physical data collected from trainings and matches. The decision of choosing a quantitative method, instead of a qualitative approach was based on two main reasons: (a) the fact that the research question is based in the physical outcomes of the players, and such measurements can be counted and quantified; (b) and because we aimed for a high reproducibility of our studies, where the results presented are likely to predict the outcome in future events under similar circumstances.

### **3.2 Institutional approval and confidentiality**

All data collected and analysed in the different Papers included in this thesis had the approval from UiT The Arctic University of Norway Institutional Review Board, written informed consent from players and approval from Norwegian Centre for Research Data. However, data was obtained from routine monitoring of athletes as a condition of their employment, which means that usual appropriate ethics committee clearance is not required (69). Furthermore, no health data was obtained.

To ensure players confidentiality in these studies, all data was anonymized before analyses.

### **3.3 User involvement and data management**

In 2015, at European Union, the three main strategic priorities for research were presented as Open innovation, Open science and Open to the world (the 3Os strategy) (70). This strategy aims to minimize the asymmetries in the ability of individuals to interact with and access science, as well as to promote a more responsible research and innovation.

According to the European Commission guidelines presented for the Horizon 2020 programme (71), researchers and end-users should work together during the whole research

period, in order to take advantage of unique perspectives and knowledge, while aligning the researcher's methodologies with the needs and expectations of the society. This programme was designed to respond to the fundamental concerns of the 3Os strategy through the implementation of several strategic orientations. Two of these orientations are: (a) the public engagement and (b) the use of Open access/data (70).

The public engagement strategy provides to end-users an easier access to scientific results, allowing them to actively participate in science and technology developments. Furthermore, the inclusion of the society during the whole research process, may be useful for researchers to raise new perspectives and have new inputs of creativity while designing the study and presenting its results. Therefore, during our project, we established interactive daily meetings (formal and informal) with the coaching staff and the players. This engagement was embedded in the research process from early stages, so that the learnings could contribute to enrich the coaching's decisions, in general, and the training process, in particular.

The Open data strategy defends that researchers should make their research data findable, accessible, interoperable and reusable (FAIR) (72). According to this source, the data management approach is the best way to promote the knowledge discovery and innovation, as well as to the data integration and reuse. This data can be, for instance, interpreted as statistics, results of experiments, observations, survey results, images and measurements. In general, a broader access to research data helps to: a) increase efficiency, by avoiding duplication of efforts; b) bring transparency to the scientific process, and consequently involve the citizens and society; c) improve the quality of previous results; and d) speed up innovation (72).

In our project, the data shared refers to the raw data (anonymized) downloaded from the ZXY Sport Tracking system<sup>1</sup> (ZXY system) (matches and training sessions). The data from our studies was then uploaded to the UiT Open Research Data (<https://dataverse.no/dataverse/uit>), which is a data archiving service for sharing, reusing and citing research data with the aim to promote open and reproducible research. By hosting the data collected, where it can be easily accessed, we aim to enhance more and quicker innovation in research.

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<sup>1</sup> ZXY Sport Tracking system: Radionor Communications AS, Trondheim, Norway – later acquired by ChyronHego.

## **3.4 Paper 1**

### **3.4.1 Study 1**

The Copenhagen Soccer Test for women was performed by 6 high-level female players (weight  $59.6 \pm 6.8$  kg, height  $171.5 \pm 4.2$  cm) using both GPS and LPM tags. The players ran the course 18 times, simulating a match and accumulating a distance of 10331 m (73). We instrumented each player with two GPS tags from GPSport SPI-ProX1 5.0 Hz system in a vest on their upper body, and two ZXY system tags placed in two small belts near the lumbar spine. Having multiple tags enables the measurement of both inter and intra-reliability of the systems.

### **3.4.2 Study 2**

12 male youth elite players (weight  $64.2 \pm 8.2$  kg, height  $176.0 \pm 6.7$  cm) were instructed to jog clockwise around the pitch at Alfheim Stadium, exactly following the side and end-lines of the pitch. All players were equipped with both the Polar Team Pro 10 GHz GPS system (Kempele, Finland) and the ZXY system. The GPS tags were connected to the anterior part of the chest by an elastic chest strap.

## **3.5 Paper 2**

### **3.5.1 Participants and match analysis**

Performance data from 23 official home matches from a Norwegian football club competing in the first tier, during two seasons (2016 and 2017) was collected for analysis. The matches were all played on the same pitch (Alfheim Stadium, Tromsø, wet artificial grass, length = 110m; width = 68 m). The sample included 18 players ( $25.2 \pm 4.4$  years;  $76.2 \pm 6.4$  kg;  $181.6 \pm 5.6$  cm; in age, body mass and height, respectively) divided into five different playing positions: CB (n = 3, observations (obs) = 35), FB (n = 5, obs = 34), CM (n = 6, obs = 38), wide midfielders (WM) (n = 3, obs = 18) and CF (n = 4, obs = 13), making a total of 138 obs. These positions were chosen according to team's main tactic formation and previous research (2, 21, 28, 29, 41, 74).

Data was analysed only if: (a) players completed the entire match, (b) the player played in the same position during all the match and (c) the team used 4-5-1 or 4-3-3 tactic formations.

### 3.5.2 Procedures

A stationary radio-based tracking system (ZXY system) was used to collect the players' match activity profiles. Each player was equipped with a specially designed belt, wrapped tightly around the waist, with an electronic sensor system at the player's lumbar spine (73). Around the stadium, where the matches occurred, there are six RadioEyes for optimal coverage, resulting in practically zero packet loss for transponders on the field. If packet loss occurred, the data was linearly interpolated. The accuracy and reliability of the system in measuring player movements in elite football competitions have been described in more detail in previous studies (7, 28, 73, 75).

### 3.5.3 Physical performance variables

Physical parameters analysed included:  $acc_{counts}$ , acceleration distance per minute – work-rate – ( $acc_{wr}$ ),  $dec_{counts}$ , deceleration work-rate ( $dec_{wr}$ ), HIR work-rate ( $HIR_{wr}$ ),  $HIR_{dist}$ , sprint work-rate ( $sprint_{wr}$ ),  $sprint_{dist}$  and turns.

The following locomotor categories were selected: HIR ( $\geq 19.8 \text{ km}\cdot\text{h}^{-1}$ ) and sprinting ( $\geq 25.2 \text{ km}\cdot\text{h}^{-1}$ ). The speed thresholds applied for each locomotor categories are similar to those reported in previous research (2, 28, 29, 39).

According to the ZXY system  $acc$  were quantified through numerical derivation from positional data with a sampling frequency of 20Hz. Furthermore,  $acc$  are defined by four event markers: (a) the start of the acceleration event is marked by the acceleration reaching the minimum limit of  $1 \text{ m}\cdot\text{s}^{-2}$ , (b) the acceleration reaches the acceleration limit of  $2 \text{ m}\cdot\text{s}^{-2}$ , (c) the acceleration remains above the  $2 \text{ m}\cdot\text{s}^{-2}$  for at least 0.5 seconds and (d) the duration of the acceleration ends when it decreases below the minimum acceleration limit ( $1 \text{ m}\cdot\text{s}^{-2}$ ).

A turn was defined as a continuous and significant rotation of the body in one direction (derived from gyroscope and compass data). When a rotation in the opposite direction is measured, that will be the end of the previous turn and the start of the next turn. Due to the angle threshold used by ZXY system, only turn  $>90$  degrees were analysed.

### 3.5.4 Statistical analysis

Descriptive statistics (means and standard deviations) were calculated for the total sample and playing position. Differences in match performance measures by field position were tested with

a one-way analysis of variance (ANOVA). When significance was found, a Bonferroni post-hoc test was performed. Effect sizes, using Cohen's *d*, was calculated and interpreted as trivial (<0.2), small (>0.2-0.6), moderate (>0.6-1.2) and large (>1.2). Significance level was set at 0.05 (76). Statistical analyses were conducted using SPSS version 24.0.

## **3.6 Paper 3**

### **3.6.1 Participants and match analysis**

Data on performance from 15 official home matches from the professional team of a Norwegian elite football club, during one season (2017), was collected for analysis. The matches were all played on (wet) artificial grass, as described previously for Paper 2.

The sample included 22 players ( $25.2 \pm 4.4$  years of age;  $76.2 \pm 6.4$  kg of body mass; and,  $181.6 \pm 5.6$  cm of height) divided into four different playing positions: CB ( $n = 4$ , obs = 37), FB/WM ( $n = 9$ , obs = 31), CM ( $n = 6$ , obs = 26) and CF ( $n = 3$ , obs = 14), making a total of 139 match observations. These playing positions were chosen according to the two tactical formations used by the team during the season. Team tactical systems and playing positions were determined by two UEFA-qualified coaches (one from the coaching staff of the team analysed) after visualizing video recordings of the sampled matches (55, 77). These observers subjectively determined the tactical systems used at the beginning of the match and verified if the formations were consistent throughout the matches (77). Furthermore, 1-4-5-1 and 1-4-3-3 formations were combined, as well as 1-3-5-2 and 1-5-3-2. This procedure was applied due to difficulties in establishing specific differences between similar playing formations when attacking and defending. When analysing the 1-3-5-2 formation, the observers noticed that the team often played in 1-5-3-2 formation when not in ball possession (defending) and in 1-3-5-2 with ball possession (attacking). On the other hand, when observing the 1-4-5-1 formation, the observers concluded that the team played in 1-4-5-1 when defending and in 1-4-3-3 when attacking (42). No other changes in formations throughout the matches were noticed by the observers, therefore no matches were excluded from the analysis.

Data was analysed only if: (a) players completed the full match (90 minutes), (b) the player played in the same position during all the match and (c) the team used 1-4-5-1 (1 goalkeeper; 2 CB + 2 FB; 3CM + 2 WM; 1 CF) or 1-3-5-2 (1 goalkeeper; 3 CB; 3 CM + 2 WB; 2 CF) tactical formations during the entire match.

### **3.6.2 Procedures**

The procedures used in this Paper, more specifically the type of tracking system and its accuracy and reliability, were the same as described previously for Paper 2.

### **3.6.3 Physical performance variables**

Physical parameters analysed included: total distance,  $acc_{counts}$ ,  $acc_{dist}$ ,  $dec_{counts}$ ,  $dec_{dist}$ ,  $HIR_{counts}$ ,  $HIR_{dist}$ ,  $sprint_{counts}$ ,  $sprint_{dist}$  and turns.

The HIR and sprinting speed thresholds are the same as presented for Paper 2 and similar to those reported in previous research (2, 28, 29). Definition and measurement protocols of  $acc$  and turns were also the same as described for Paper 2.

### **3.6.4 Statistical analysis**

The results are presented as mean and 95% confidence interval, unless otherwise stated. A linear mixed-effects model with restricted maximum likelihood estimations was used to examine differences in LPM-derived variables and match duration between 1-3-5-2 and 1-4-5-1 formations. Mixed models can account for unbalanced repeats per player and thus used to model the data. Tactical formation, playing position and their interaction was modelled as fixed effects (effect describing the association between the dependent variable and covariates), while ‘athlete ID’ was included as a random effect (effects generally representing random deviations from the relationships of the fixed part of the model). An  $\alpha$ -level of 0.05 was used as level of significance for statistical comparisons. Furthermore, multiple comparisons were adjusted using the Tukey method. The t-statistics from the mixed models were converted to effect sizes correlations (78). Effect sizes were interpreted as <0.1, trivial; 0.1–0.3, small; 0.3–0.5, moderate; 0.5–0.7, large; 0.7–0.9, very large; 0.9–0.99, almost perfect; 1.0, perfect (79). All statistical analyses were conducted using the lme4, lsmeans and psychometric packages in R statistical software (version 3.4.1, R Foundation for Statistical Computing Vienna, Austria).

## **3.7 Paper 4**

The main computer science professional society ACM defines the field of computer science into three disciplines corresponding to different research paradigms (80):



- *Theory* stems from mathematics, and studies objects whose properties and relationships can be clearly defined and reasoned about using logical reasoning.
- *Abstraction* stems from experimental science, and constructs models based on hypotheses or through inductive reasoning about observable objects or phenomena. The model is evaluated by comparing its predictions to experimentally collected data.
- *Design* stems from engineering and uses a systematic approach to construct systems or devices that solve specific problems in an experimental context.

In practice, these disciplines are intertwined, and computer systems research draws upon all three paradigms with varying degrees. Paper 4 is based on the design paradigm, emphasizing the construction of the actual software artefact Metrix to substantiate conclusions based on experiments and user evaluations.

Metrix is a prototype software system primarily developed at the computer science department of UiT, The Arctic University of Norway, to allow coaches and practitioners to quantify and control the players' external load during trainings and matches. The system functionalities were implemented based on certain requirements, needs and feed-back given by professional coaches of a top-level football club in Norway. This web application can be accessed by users through normal web browsers, so practitioners can use different types of portable devices (e.g. smartphone, PC, tablet, etc.).

### **3.7.1 Data sources**

The main data source used is the player activity profile during matches and trainings collected through ZXY system. The description, accuracy and reliability of this tracking system were described previously for Paper 2.

Before every match or training, the sensor belts are distributed to the players and activated when the session starts. At this point, Metrix and ZXY system start connecting, with the first receiving raw sensor data records through a transmission control protocol connection. Therefore, the output data records presented in Metrix include the measurements of a specific ZXY transponder. The players wear exactly one belt each, and the transponder in each belt is identified by a tag id.

Even though a ZXY data record is comprised by a total of 16 data fields (e.g. positioning, direction, speed, etc.) in Metrix we only take into consideration a smaller array of key

performance indicators (e.g. current player's speed, cumulative distance, cumulative number of accelerations, etc.) as suggested by the coaches involved in the project.

### 3.7.2 Event model

Even though a variety of events and metrics are plausible to be extracted from the sensor data, for the purpose of this Paper only two classes of movement data were used: run events and acceleration events. The definition and measurement protocols of both run and acceleration events are the same as described for Paper 2.

### 3.7.3 User interaction

Users have several interfaces available in order to interact with Metrix. One of these interfaces is the *Week Planner* which allows coaches, for instance, to establish goals for different players or different playing positions. For example, a coach may require the CF, during the microcycle, to achieve 90% of  $HIR_{dist}$  and 110% of  $acc_{counts}$ , of the match demands of the CF playing position. The percentage is calculated based on each player's all-time best match performance of each variable used. For example, if the player's highest  $HIR_{dist}$  performed in an official match was 1,000m, the target of 90% established by the coach to achieve during the microcycle, means that the player is expected to accumulate a total of 900m of  $HIR_{dist}$  during that specific period of time. With this way of quantifying specific TL, practitioners may benefit from a deeper and better player monitoring. The initial best-performance values are gathered from historical match data, provided by the ZXY system.

The established goals can be controlled using the *Metrix Live Session* interface, which organizes player data in visual structures called *cards*. A player's card presents live data when he/she is participating in an on-going match or practice. The cards are updated in real-time (with 3 sec delay) according to the data received from ZXY system, allowing coaches to verify if the planned workload of individual players has been exceeded or not.

Moreover, another interface provided is called the *Video Service* and allows the users to request video playback of certain events during an on-going session (e.g. replay the moment when a player achieved the top-speed of that session). This service is based on the Bagadus system (81), that records and stores video data from the football pitch on a daily basis.

## 3.8 Paper 5

### 3.8.1 Participants and match analysis

Players performance data (18 outfield players) from 15 official home matches and 11 in-season microcycles was collected for analysis, and players divided into four different playing positions: CB ( $n=4$ ;  $M_{obs}=42$ ;  $T_{obs}=141$ ), WB ( $n=3$ ;  $M_{obs}=21$ ;  $T_{obs}=101$ ), CM ( $n=5$ ;  $M_{obs}=40$ ;  $T_{obs}=162$ ) and CF ( $n=6$ ;  $M_{obs}=32$ ;  $T_{obs}=133$ ). These positions were chosen according to team's tactical formation (1-3-5-2) and previous research (2, 21, 41).

### 3.8.2 Procedures

TL and ML data were collected using the same stationary radio-based tracking system previously specified in Papers 2 and 3. Match activity profiles, per position, in 15 official home matches, during the season 2018, were characterized. Match data (excluding warm-up) was analysed only if: (a) players completed, at least 60 min of the match, and (b) the player played all the time in the same position. Match activity based on samples of less than 90 min were extrapolated to 90 min. We adapted the inclusive and extrapolation criteria from Stevens et al. (82), using the match data from players who played for at least 60 min. External load data of 11 typical microcycles (four football training sessions within the six days-period between matches) was collected and analysed per position. Players without  $M_{obs}$  were not included in the sample, and  $T_{obs}$  from players who did not finish the training session were also excluded from analysis. All training sessions were composed by warming-up exercises and a combination of technical drills, small-sided games, finishing drills and tactical exercises.

The team used in this study rarely played more than one match per week (participating only in the national league and cup). However, many breaks during the season (FIFA International Match Calendar, Summer break, etc.) led to a smaller number of "typical weeks" tracked (one match per week with six full days between matches) (82, 83) than what was expected. These typical microcycles often included two days-off (MD+1 and MD-2) and four training sessions. Only the main team sessions were considered. This refers to the training sessions where both starting and non-starting players trained together. Consequently, other types of sessions were excluded from analysis, including recovery sessions (MD+1), individual and conditioned training, as well as additional training for non-starters (MD+1).

### **3.8.3 Physical performance variables**

Physical parameters analysed included:  $acc_{counts}$ ,  $dec_{counts}$ ,  $HIR_{dist}$ ,  $sprint_{dist}$ , 5-min peak of accelerations ( $acc_{peak}$ ), 5-min peak of decelerations ( $dec_{peak}$ ), 5-min peak of HIR distance ( $HIR_{peak}$ ) and  $sprint_{peak}$ . The HIR and sprinting speed thresholds are the same as presented in Paper 2 and similar to those reported in previous research (2, 28, 29). Definition and measurement protocols of acc and dec were also the same as described in Paper 2.

### **3.8.4 Statistical analysis**

The results are presented as mean and standard deviation, unless otherwise stated. A linear mixed-effects model with restricted maximum likelihood estimations was used to examine differences in LPM-derived variables (sum or peak) between training and match by position. Mixed models can account for unbalanced repeats per player and thus used to model the data. The fixed effects in the models included session type, playing position and interaction term, while 'athlete ID' was included as a random effect. Thus, each athlete had a subject-specific intercept. An  $\alpha$ -level of 0.05 was used as level of significance for statistical comparisons. Furthermore, multiple comparisons were adjusted using the Tukey method. The t statistics from the mixed models were converted to effect size correlations (84). Effect sizes were interpreted as <0.1, trivial; 0.1-0.3, small; 0.3-0.5, moderate; 0.5-0.7, large; 0.7-0.9, very large; 0.9-0.99, almost perfect; 1.0, perfect (79). All statistical analyses were conducted using the `lm4`, `lsmeans` and psychometric packages in the software R (85) were used for the analysis.

## 4 Summary of the results

### 4.1 Radio-based wearable positioning data system (Paper 1)

In study 1, the average total distance covered was measured by GPSport SPI-ProX1 to  $11,668 \pm 1,072$  m with a CV value of 6%, while ZXY system measured the distance to  $10,204 \pm 103$  m with a CV value of 1%. For HIR ( $>16.0 \text{ km}\cdot\text{h}^{-1}$ ), the values were  $612 \pm 433$  m with a CV value of 37.4% and  $1,238 \pm 38$  m with a CV value of 3.1%. In the intra-reliability test, the measured discrepancy between the two tags placed on the same player ranged between 800 and 2,071 m using SPI-ProX1 and 25-290 m using ZXY system.

In the jogging part of study 2, the GPS tracks can clearly be seen to deviate significantly from the actual trajectory of the players, while the tracks derived from ZXY system much more closely follow the side and end lines of the football pitch. Furthermore, in the training session, sprint performance was measured lower by ZXY system ( $55.3 \pm 7.3$  m) compared to Polar Team Pro ( $70 \pm 12.9$  m) ( $p>0.05$ ).  $\text{HIR}_{\text{dist}}$  and  $\text{acc}_{\text{counts}}$  showed an inverse tendency with higher values:  $222.8 \pm 77.8$  m and  $100.9 \pm 19.9$  counts vs.  $164.4 \pm 54.9$  m and  $81.0 \pm 15.9$  counts (ns).

### 4.2 Position specific player load in match-play (Paper 2)

In relation to acc and dec profiles, there were similar patterns in the work-rate of both variables, with CB and CM performing the least of all playing positions. Moreover, WM presented higher values ( $76.7 \pm 12.1$ ;  $86.1 \pm 14.7$ ) in  $\text{acc}_{\text{counts}}$  and  $\text{dec}_{\text{counts}}$  than CB ( $64.9 \pm 9.7$ ;  $61.5 \pm 10.8$ ) and CM ( $65.8 \pm 15.6$ ;  $71.5 \pm 20.6$ ) ( $p<0.001$ ), respectively.

Differences were observed in  $\text{sprint}_{\text{wr}}$  between CB ( $0.9 \pm 0.5$  m/min) and all other positions, especially when compared with CF ( $2.5 \pm 1.0$  m/min) ( $p<0.001$ ).

Regarding  $\text{HIR}_{\text{dist}}$  CF presented higher values in 26-30 m ( $4.3 \pm 1.2$ ) than all the other playing positions, while distances of 36-40 and 46-50 m were covered more times by FB ( $1.7 \pm 1.4$ ;  $0.9 \pm 1.0$ ). Distances of 1-5 m in HIR were the distances covered more often by CB, CM, WM and CF, whereas FB had higher values in distances of 6-10 m. Furthermore, there was a pattern of covariance in the work-rates analysed (acc, dec, HIR and sprint) across playing positions.

The main outcome from the analysis of turns, was that CB were the players with the least amount of turns per match ( $32.7 \pm 10.1$ ), significantly less than FB ( $41.0 \pm 12.1$ ) and WM ( $42.9 \pm 12.3$ ) ( $p=0.009$ ).

### **4.3 Differences in match demands between tactical systems (Paper 3)**

CB presented higher values in almost all the variables when playing in 1-4-5-1, however, only in  $HIR_{counts}$  ( $36.1 \pm 3.5$ ) this difference was significantly higher than in 1-3-5-2 ( $28.2 \pm 3.5$ ) ( $p=0.008$ ), with a correspondent medium effect size ( $r = 0.37$ ).

No significant differences were observed between the tactical formations analysed from players playing in wide positions (FB/WM/WB) and CF. Regarding CM, small effect sizes were observed in  $HIR_{counts}$  ( $r = 0.12$ ) and  $acc_{counts}$  ( $r = 0.14$ ) with higher values being performed when playing in 1-4-5-1 ( $38.5 \pm 3.2$ ;  $62.3 \pm 5.5$ ) compared to 1-3-5-2 ( $35.7 \pm 3.4$ ;  $55.9 \pm 5.9$ ).

Significant differences were found in various parameters when comparing the physical performance of the whole team when playing with different tactical systems. Significant higher values were observed in  $HIR_{counts}$  ( $r = 0.25$ ) and  $sprint_{counts}$  ( $r = 0.22$ ) when playing in 1-4-5-1 ( $43.6 \pm 1.9$ ;  $11.4 \pm 1.1$ ) compared with 1-3-5-2 ( $40.0 \pm 2.0$ ;  $10.0 \pm 1.1$ ) ( $p=0.005$  and  $p=0.0015$ , respectively). Furthermore, when playing in 1-4-5-1, the team was observed to perform more  $acc_{counts}$  ( $75.8 \pm 3.2$ ) and  $dec_{counts}$  ( $77.8 \pm 3.5$ ), as well as covering higher deceleration distances ( $dec_{dist}$ ) ( $440.3 \pm 23.3$ ) than when playing in 1-3-5-2 ( $71.1 \pm 3.4$ ;  $72.5 \pm 3.6$ ;  $413.7 \pm 24.2$ ; for  $acc_{counts}$ ,  $dec_{counts}$  and  $dec_{dist}$ ) ( $p=0.022$ ;  $p=0.014$ ; and  $p=0.032$ , respectively).

### **4.4 Metrix (Paper 4)**

#### **4.4.1 Latency analysis**

To evaluate the performance of Metrix it is necessary to analyse the capacity of the system in processing the physical performance parameters and delivering the data in real-time. The real-time delay in ZXY system is approximately 3 sec. Since the increase in the number of players being tracked leads to an increase of the sensor data input volume, two different and realistic scenarios were analysed: a training session (25 players) and an official match (10 players).

For the match experiment, a total of 221 events were captured, while in the training experiment we observed a total of 525 events. Results observed show a linearly increase of the end-to-end latency when increasing the number of players, with the training session presenting almost the double ( $\sim 100$  m/s) of the latency observed in the official match ( $\sim 50$  m/s). However, this experiment was made with an unrealistic high number of users (up to 1,000). This means that in a normal situation with only two or three users running Metrix simultaneously, this latency drastically decreases to less than 10 m/s.

#### **4.4.2 User evaluation**

Metrix was developed for football practitioners and so, a user questionnaire was considered the best method to evaluate its value. This survey was divided into three main categories: functionality, design and overall interest. To answer a total of 11 questions, a balanced five-point Likert scale was used by the four UEFA qualified coaches who took part of this survey.

The main results refer to the fact that coaches consider Metrix as a useful tool to improve the objective monitoring of player load, as well as to achieve the established weekly training goals. Furthermore, the users recognised a user-friendly interface, where the inclusion of daily/weekly progress bars give an easier understanding of the player's performance data.

### **4.5 Training load vs Match load (Paper 5)**

#### **4.5.1 Accumulated training load**

CF was the only playing position which presented significant differences between matches and microcycles, in all the four variables analysed. More acc and dec were performed during training sessions ( $112.3 \pm 5.8$  and  $94.1 \pm 5.9$ ) than in matches ( $78.5 \pm 6.2$  and  $74.3 \pm 6.3$ , respectively). Furthermore, the inverse was observed in  $HIR_{dist}$  and  $sprint_{dist}$ , with higher distances being covered during matches ( $897.1 \pm 62.6$  and  $171.7 \pm 1.0$ ) compared to trainings ( $561.0 \pm 59.3$  and  $104.6 \pm 0.9$ , respectively).

Even though, WB did not present significant differences in  $acc_{counts}$  neither in  $dec_{counts}$ , statistically lower values of  $HIR_{dist}$  and  $sprint_{dist}$  were observed in the microcycles ( $564.9 \pm 76.4$  and  $85.8 \pm 1.2$ ) than in matches ( $984.7 \pm 82.9$  and  $238.2 \pm 1.3$ , respectively).

When expressing the estimated cumulative load per variable as a percentage of tracked match values (100%), it is possible to observe that match demands were largely overperformed for  $\text{acc}_{\text{counts}}$  (131-166%) and  $\text{dec}_{\text{counts}}$  (108-134%), by all the playing positions. However, relative to match values, training values for  $\text{sprint}_{\text{dist}}$  and  $\text{HIR}_{\text{dist}}$  were considerably lower (36-61% and 57-71%) than those previously reported for acc and dec.

#### **4.5.2 Most demanding passages of play (5-min peaks)**

Significant differences between matches and trainings were observed only in  $\text{acc}_{\text{peak}}$  of CB ( $6.4 \pm 0.4$  and  $7.5 \pm 0.4$ ) and CM ( $6.2 \pm 0.4$  and  $7.7 \pm 0.4$ , respectively). However, WB presented slightly higher values of  $\text{HIR}_{\text{peak}}$  and  $\text{sprint}_{\text{peak}}$  in matches ( $119.0 \pm 9.6$  and  $56.7 \pm 6.7$ ) than in trainings ( $84.3 \pm 8.6$  and  $36.3 \pm 6.0$ , respectively). All the other playing positions and peak variables presented similar values between matches and microcycles.

Moreover, in  $\text{acc}_{\text{peak}}$  and  $\text{dec}_{\text{peak}}$  the percentages did not differ largely between playing positions (range: 102-124% and 88-115%, respectively), with CB and CM performing slightly higher values (relative to their specific match demands) than WB and CF. However, the biggest difference observed between playing positions is for  $\text{sprint}_{\text{peak}}$ , with WB achieving, during the microcycles, only 64% of the most demanding 5-min sprinting in matches, while CB, CM and CF levelled and overperformed the match values (107%, 100% and 107%, respectively).



## 5 Discussion

### 5.1 Accuracy and reliability of tracking technology used

The use of various tracking systems in elite football teams is getting more and more common, both in trainings and matches. In this domain, GPS based technology has traditionally been the preferred choice by clubs to quantify training load of team-sports athletes (86). However, in Paper 1 we show why we have preferred to use an LPM radio wave-based system (ZXY system) instead. In this Paper, the study with female players running the Copenhagen Soccer Test for women presented a large difference of the average total distance covered between the SPI-ProX1 (GPS) and the ZXY system, with the CV-values being 6% and 1%, respectively. Although the test has a 10,331 m pre-set course that players should follow, some small differences in the measured distance may be expected independent of the tracking system used. However, while ZXY system reported slightly lower values ( $10,204 \pm 103$  m), the considerably higher values ( $11,668 \pm 1,072$ ) presented by SPI-ProX1 compared to the true track distance and in addition the larger discrepancy between units (intra-reliability test), suggest that results obtained with this GPS model should be interpreted with caution. These discrepancies become even larger when analysing high-intensive actions, such as HIR ( $>16.0 \text{ km}\cdot\text{h}^{-1}$ ), with SPI-ProX1 presenting less than half of the distance recorded by ZXY system ( $612 \pm 433$  m vs.  $1,238 \pm 38$  m) with CV values of 37.4% and 3.1%, respectively.

Furthermore, the intra-reliability test also shows a much lower consistency of the SPI-ProX1, since the discrepancy between the two tags placed on the same player, ranged between 800-2,071 m, compared to only 25-290 m when using ZXY system. Our observation that the SPI-ProX1 system apparently measure higher values for total distance covered is further supported by a previous research where 19 elite junior players were equipped with both SPI-ProX1 and ZXY system during a football match. In this experiment, the average total distance measured by SPI-ProX1 was also higher ( $10,805 \pm 847$  m) than the measured by ZXY system ( $9,891 \pm 974$  m) (87).

In order to test the accuracy and reliability of another GPS system, in Paper 1 we also performed a study where youth elite players have jogged on the side and end lines of the pitch, wearing both a Polar Team Pro 10GHz GPS system and the ZXY system. The GPS tracks obtained significantly deviated from the actual trajectory of the players, while the image of ZXY system much more closely follow the lines. A similar effect was also observed in previous

research (88). Moreover, the higher challenges of measuring high-intensive actions with GPS systems, as mentioned previously, were also observed in this study. During the training session completed by seven of the elite youth players, the  $\text{sprint}_{\text{dist}}$  measured by Polar Team Pro ( $70.0 \pm 12.9$  m) was significantly higher than by ZXY system ( $55.3 \pm 7.3$  m). Interestingly,  $\text{acc}$  ( $\geq 2 \text{ m}\cdot\text{s}^{-2}$ ) showed an inverse tendency.

As a reason or justification for all these differences, it could be speculated that the GPS signal reception at Alfheim Stadium is poor. However, the stadium does not have an overhanging roof, nor are there any nearby high buildings. A plausible explanation that must be taken into consideration is the arctic location of the stadium at  $69.65^\circ$  north. Accordingly to previous authors (89), the inclination of the GPS satellite orbits is approximately  $55^\circ$  (north or south), so no satellites have been directly overhead during our tracking sessions. However, this error rates cannot be fully justified by location, since higher errors for inter-unit reliability have also been reported in previous research, across different GPS systems (90, 91). Our findings, supporting the use of LPM instead of GPS at the stadium where all tracking was conducted, due to their superior accuracy, are in line with previous research (6). It remains unclear to what extent the low accuracy and reliability in the GPS systems limits its usefulness for quantification of TL and ML. Therefore, coaches and practitioners should carefully reflect about the pros and cons of the use of GPS, as the player and team load management can be severely compromised. Taking into consideration the large intra/inter unit differences in running profiles presented in Paper 1 and independent of the system used, we strongly recommend the assignment of a specific device to each athlete, in order to minimize the within-athlete longitudinal monitoring error and maximize the meaningful interpretation of the data.

## **5.2 Specificities of match physical demands**

### **5.2.1 Playing positions**

The results presented in Paper 2 show that physical demands put on elite football players in official matches vary greatly across playing positions. A novel finding from this study was that the work-rates in HIR, sprints,  $\text{acc}$  and  $\text{dec}$  fluctuates in the same pattern across playing positions. Our results demonstrate that CB and CM had significantly lower work-rate in sprints,  $\text{acc}$  and  $\text{dec}$  than FB, WM and CF, with CB also having lower  $\text{HIR}_{\text{wr}}$  than these three playing

positions ( $p < 0.001$ ). Previous research has similarly presented CB covering lower high-intensity and sprinting distances than FB (2, 38, 41, 92).

In our study, wide positions (FB and WM) presented higher work-rates in acc, dec and sprints than more central positions (CB, CM and CF), which is in line with previous studies reporting greater  $\text{HIR}_{\text{dist}}$  and  $\text{sprint}_{\text{dist}}$  covered by wide players (2, 28, 38, 92). However, the differences observed between CF and WM in  $\text{HIR}_{\text{wr}}$  are not consistent within the literature, with a study of English Premier League teams supporting our results (41), but others presenting results in opposition to our findings (2, 42, 92). It has been argued within the research literature that these differences between central and wide positions appear due to the lack of space in central areas for reaching sprinting velocity, as well as the team's playing style (different roles for different positions) (28, 93, 94). Therefore, we conjecture that the specific context of the club where our data was collected and the playing style adopted (playing mostly with a low block and seeking for counter-attacks) have to a certain extent influenced the position's specific physical demands observed.

A novel approach of this Paper was to accurately measure the length of the runs performed by the different positions at high speeds ( $>19.8 \text{ km}\cdot\text{h}^{-1}$ ). To the best of our knowledge, no previous research has characterized players' running profiles regarding specific distances covered per HIR in official matches, across different playing positions. The data shows that player position had a significant influence on the different distances covered in HIR and sprints. While HIR between 1-5 m was the most common for the majority of the playing-positions (CB, CM, WM and CF), for FB it was 6-10 m. Slightly different patterns appear in the sprinting profiles ( $>25.2 \text{ km}\cdot\text{h}^{-1}$ ), with CF being the position who performs more often longer runs (6-10 m) and FB presenting similar profiles to CB, CM and WM, covering more often shorter distances (1-5 m) in sprints. These differences in the distance and consequently in the duration of the high intensity efforts are shown in the literature to have an effect on the intermittent nature of the game (1). For instance, some authors (95) found that longer sprints (over than 30 m) also demanded longer recovery time than shorter sprints (10-15 m). This increased recovery time was described as being 47% higher than the recovery for the regular sprints.

A clear conclusion possible to draw from the positional differences presented in Paper 2 is that, in the context of this team, CF is the most physical demanding position with longer distances covered in HIR, sprints, accelerating and decelerating than all the other positions. Another finding refers to the acceleration profiles, with CF and WM accelerating more often compared with other positions, which differs from a previous study with another Norwegian

professional football club using the same tracking system in matches (28). Despite the different acceleration profiles outcome, these two studies also show similar trends, for instance CB being the players who decelerated the least times. In our study, in almost all the positions (CB, FB, CM and WM), slightly lower values of  $acc_{counts}$  were observed compared to the results presented by other authors (28, 60, 93). An inverse trend was observed in  $dec_{counts}$  with our study presenting higher values for all the positions, most likely caused by the style of play and various sampling technology.

The use of only distance and speed may underestimate the calculation of external player workload since this type of time-motion analysis has neglected some essential and specific football movements (e.g. turns). Previous research has also mentioned the importance of the frequency, duration, distance and angle of turns of the specific football efforts across playing positions, to the prescription metrics when planning training sessions (4). In our project, this challenge was taken into consideration and the frequency and turn angles were also quantified. The frequency of turns observed in Paper 2 were considerably different from those reported in previous research (40). In fact, and even though our study has quantified only turns  $>90^\circ$  (angle threshold defined by ZXY system), attackers (CF) presented a mean of  $\sim 42 \pm 13$ , midfielders (CM and WM) performed  $\sim 39 \pm 13$  and defenders (CB and FB)  $\sim 37 \pm 12$ , while previous research (40) reported much higher values for attackers ( $\sim 101$ ), midfielders ( $\sim 107$ ) and defenders ( $\sim 97$ ) in turns  $>90^\circ$ . Conflicting results are also possible to find in the differences observed between playing positions, since Bloomfield et al. (40) reported midfielders performing significantly fewer turns during a match than defenders and strikers, while in our study such differences were not noticed.

The lack of research in the literature within this domain (acc and turns), the different cultural and competitive contexts and the different sampling technologies used, make these comparisons between studies difficult to draw. Therefore, results should be interpreted with caution.

## **5.2.2 Tactical systems**

The specificities of match physical demands should not be explained only through the different playing positions of the players. In Paper 3 we explored the influence of the tactical system adopted in the match demands across playing positions, which is an area of research that is not well described in the literature. The comparisons were made according to: (a) playing positions and (b) whole team.

The results suggest that general match physical demands do not significantly differ between the two tactical formations analysed (1-3-5-2 and 1-4-5-1), when compared by playing position. In both formations, players presented similar profiles in almost all the physical parameters analysed. However, there were some exceptions, and the most relevant were the higher  $HIR_{counts}$  performed by CB when playing in 1-4-5-1, and the longer  $HIR_{dist}$  presented by wide positions (FB/WM/WB) in 1-3-5-2, with a medium and small effect size, respectively. In relation to CB (1-4-5-1), such difference occurred probably due to the larger area they needed to cover when compared to the area covered by three CB when playing in 1-3-5-2. More specifically, when in defensive organisation (without ball possession), the defensive line of three CB usually became a defensive line composed by five players (three CB and two WB). This means that the increased number of players playing in the defensive line leads to less  $m^2$  per player to cover. On the other hand, players in wide positions presented longer  $HIR_{dist}$  when playing in 1-3-5-2, most likely due to the fact that in this formation the team played only with two players on the wide flanks (WB), and they needed to cover all the flank, while in 1-4-5-1 formation those corridors were simultaneously covered by a total of four players (two on each side).

A contradictory result observed in our study relates to the CF general work-rate. It has been speculated by other authors (96) that CF have higher physical demands in match-play when playing “alone” in the offensive line (e.g. 1-4-5-1; 1-5-4-1), since they apparently are very often isolated and marked by several opponents. Despite that we have hypothesised that the same pattern might occur in our study, the results presented in Paper 3 suggest a different explanation and/or a need for further research. Higher, though not significant, values can be observed in  $HIR_{dist}$  and  $sprint_{dist}$  for CF when playing with two attackers (1-3-5-2) compared with playing with only one (1-4-5-1).

Furthermore, in order to exclude possible bias, we also compared the playing time (substitutions) between the two formations, and no differences were observed in any of the playing positions.

When playing position was not taken into consideration and the match load of the whole team was analysed, the results show significant differences between the two tactical systems. When playing in 1-4-5-1, the team performed, on average, more runs above  $19.8 \text{ km}\cdot\text{h}^{-1}$  ( $HIR_{counts}$  and  $sprint_{counts}$ ) and a higher number of acc and dec. In general, almost all variables analysed presented higher values during the first period of the season (1-4-5-1) than in the second. These discrepancies raise the contextual challenges faced during these studies, which will be discussed later in this thesis.

According to previous research (35, 97), there is a trend, among winning teams, to relax and decrease their work-rate in the latter stages of matches. On the other hand, although teams who are losing the match may increase their work-rate during a short period of time (98, 99), they may quickly lose the motivation to keep the elevated work-rate, which has been proved to be true especially when the goal difference increases negatively (conceding more goals) (100). The differences observed between these two tactical systems may be justified by the significant discrepancy between the score line and match final results achieved during the two periods when the different tactical formations were used: first part of the season (1-4-5-1) and final part of the season (1-3-5-2). The team collected a total of seven points, result of one victory, four draws and three defeats in the first eight home matches played. After that, on the last seven home matches and with the change of tactical formation to 1-3-5-2, the team accumulated a total of 16 points, result of five victories, one draw and one defeat. The match results (considerably more draws) and the differences in style of play may partly explain the higher work-rate observed when playing in the 1-4-5-1 tactical formation.

### **5.3 Training specificity**

The data presented in Papers 2 and 3 shows that speed and distance measures only to some extent predict the physical demands of a football player and that these demands vary significantly across playing positions. Taking into consideration the law of training specificity (67) and the idea that the physical loading of training sessions should be individually designed to improve performance and avoid the status of under or overtraining (101), the coaches need a clear view on how different playing positions achieve load not only in matches but also combined with practices.

Therefore, in Paper 5 we objectively quantified and compared, per playing position, the weekly training load and most demanding passages of play (5-min peaks) with match demands. Consistent with our hypothesis, large discrepancies in  $HIR_{dist}$  and  $sprint_{dist}$  were observed between TL and ML. The distances performed at the most demanding speed thresholds were much lower in microcycles than in matches, while the number of acc and dec during training weeks were considerably higher than match values. These differences were expected, since most of the exercises applied in trainings are played in small areas, which means that change of directions and acc are frequently required (102). Therefore, if analysed separately, acc and

dec would overestimate the work done by the players in training sessions, as well as the opposite (underestimate) would be noticed if only the distance ran at high speed was used (103).

In order to help the training prescription and the communication between coaches and players, recent research (82, 83) has suggested an interpretation of TL, using ML as a reference (100%). The relative training values presented in this study, show that match demands were overperformed for  $acc_{counts}$  (131-166%) and  $dec_{counts}$  (108-134%) but underperformed for  $HIR_{dist}$  (57-71%) and  $sprint_{dist}$  (36-61%). Similar discrepancies between the accumulated weekly load of different variables were reported in previous studies using Dutch (82) and Portuguese (83) football teams. These findings suggest that currently, the training drills used tend to emphasize some physical variables, such as acc and dec, and neglect others, like HIR and sprints. Practitioners should be aware of and take into consideration how different pitch size, shape, number of players, etc. dictate the external and internal training load accumulation.

Even though the ability to perform high-intensity exercise has been proved to be strongly correlated with success in football (17, 84), other research have shown that high training loads are related to the increase of injury risk (104, 105). In fact, differences between trainings and matches may be expected, since simply reproducing match demands during practices would oversimplify the complex process of developing elite players. However, it is very unlikely that trainings with consistently lower distance covered in the most demanding speed thresholds, compared with competitions, offer an appropriate stimulus for players adaptation to the higher match demands (106). Moreover, acc and dec have been proved to cause greater neural activation of the muscles as well as higher metabolic demands, compared to constant speed running (107-110). Therefore, the risk of overtraining or the increment of the injury risk may not be a problem when considering to increase the  $HIR_{dist}$  and  $sprint_{dist}$ , if followed by a decrease in  $acc_{counts}$  and  $dec_{counts}$  in trainings.

In a study with a Spanish football team (57), the authors concluded that the physical demands of the most demanding passages of play are position-dependent. Therefore, developing training programs based only on absolute or average match values may limit specificity and underestimate the real demands of the most demanding passages of competition. Compared to the weekly accumulated load, differences between variables were minimized and match values replicated when taken into consideration only the 5-min peaks of microcycles. However, one exception was observed, with WB presenting considerably lower values of  $sprint_{peak}$  (64%) and  $HIR_{peak}$  (71%) than the other positions, suggesting that the players in this playing position may not be prepared for the worst-case scenarios in matches. This difference may be caused by the fact that, from all playing positions, WB are the players who were

required to perform the highest  $\text{HIR}_{\text{peak}}$  ( $119 \pm 9.6$ ) and  $\text{sprint}_{\text{peak}}$  ( $56.7 \pm 6.7$ ) in matches. Therefore, if coaches and practitioners aim to prepare these players for the worst-case scenarios of competition (specificity), training stimulus in these particular variables should be increased.

Such specificity can be achieved through on-field training methods that aim to match or exceed the match demands in all the performance components (tactical, technical, physical and psychological) (64). Bradley et al. (4) referred that isolating tactical conditioning drills to specific positional demands is a highly effective training approach, since it allows a close replication of the most demanding periods of the match. However, while targeting the development of physical capacities, it is crucial to include balls in the exercises, in order to increase the complexity by adding the technical component, as well as trying to connect all the playing positions to develop tactical behaviors (111). Readers may keep in mind that football is a collective sport and so, combination/collective drills must still be used, especially if the aim of the exercise/training is the players' global performance and not just a physical stimulus.

## 5.4 Supplemental data sources

The studies described throughout this thesis provide new insights about the importance of using tracking systems in practices and matches, and how to adapt and individualize training sessions according to the match load. However, as mentioned in Paper 1, tracking technologies do not fully guarantee an accurate measurement of player locomotor activities, and so, the calculation of player and team load can be biased. In order to minimize the eventual problems caused by this, and to provide coaches and practitioners with new and useful information, we have developed one cyber-physical system (Paper 4) and experimented with other two specific supplemental data sources (Paper 1) which we expect to integrate in future studies.

The system developed (Metrix) appears as a solution given to practitioners, to solve part of the challenges identified in the previous Papers. This system provides coaches with a toolkit to individualize training goals for different playing positions, or for individuals. In fact, match analysis in football is defined as the objective measurement and analyse of discrete events during trainings and matches (112). This structured process, which started with a time consuming notational analysis (pen and paper based) has evolved into a more classic video-based time-motion analysis (30). The advancements of digital technology have brought into the market an array of different data collection methods. However, most existing methods are based on post-game analysis, which restricts coaches to review games or practices in retrospect. To



the best of our knowledge, there are only few that perform quantified data based real-time analysis, allowing coaches to act immediately and not only *a posteriori*. This live feedback allows coaches to better control the players who are pushing themselves over the pre-established weekly goals or to give additional physical load to those who did not reach the training targets. Metrix also provides users with an option for coupling sport events with video recordings, which allows coaches to view replays of specific player performed events. Even though the promising results of the network latency analysis, readers must be aware that in a real-world deployment, general latency is expected to slightly increase, depending on factors such as users' bandwidth and their proximity to the server. Nevertheless, the increased network latency is expected to stay within the range of 10 to 100 m/s, which is considered sufficient for practical use, since coaches are not expected to react or give feedback any quicker.

In relation to the additional data sources experimented with, the first refers to a full-stadium video coverage that provides videos of teams' collective behaviours and players actions. These videos have traditionally been obtained from professional TV broadcasts, hand-held cameras or fixed arena cameras. These sources have some undesired challenges, for instance, the lack of availability for practices, the need of man-power or the high cost, etc. More importantly, none of these solutions, provide coaches a sufficient high-resolution tactical view over the pitch, which means a good coverage of all players on the pitch. Therefore, our video supplemental data source has been the Bagadus video system (81).

Bagadus with its array of multiple small shutter and exposure synchronized cameras records a high-resolution video of the entire football pitch. In this system, the video playback can switch streams delivered from the different cameras, either manually by selecting a camera, or automatically following players based on sensor information. It can also play back a panorama video stitched from the different cameras. With the panorama video, a virtual view can also be extracted (113), for instance to automatically follow a specific player (114).

In elite football, the match tactical analysis has become more and more important and that is reflected on the time spent by coaches and analysts working on manual post-game analysis by watching full-length recordings of the match. Bagadus, on the other hand, enables a much more efficient video retrieval and summarizing experience, reducing drastically the time used by coaches to identify and locate relevant video segments. At Alfheim Stadium, where all these studies were developed, the interaction between the tracking system used (ZXY system) and Bagadus has been particularly useful, as it enables to track individuals or groups of players and, for instance, collect a video summary of all situations where a particular player sprints towards the opponent's goal, or all the situations where the CF is on his own half (115).

Furthermore, in addition to positional data, an annotation system was developed (81, 116) for use during matches to tag important events with metadata as they occur. These tagged events are time-aligned with the video and enable video-based team or individual feedback after training sessions or in the locker room during match half-time.

The last data source suggested is a Player Monitoring System (PMSys) (11), which enables the monitoring of the individuals' global wellness and subjective internal load (rated perceived exertion - RPE), through repeated questionnaires. In addition to the app used by the players, coaches can use a web-portal to analyse the data. The portal is 'user-friendly' and provides several tools and plots for team and individual players, so the coaches can easily 'read' the data and analyse only the information needed. This additional data source may help coaches to better control TL, as well as to deal with the increasingly common congestive schedules (117). In fact, the usefulness and importance of the use of RPE reports for the management of TL is shown in previous research, which have, for instance, used RPE reports to quantify and profile the training and match loads of international footballers (118). Moreover, other authors have concluded that RPE is moderately-to-largely correlated to objectively measured load variables (119). At elite levels, complimenting LPM positional data, like the ones used in all five Papers, with self-reporting tools (wellness and RPE) may, therefore, help to optimize the player management and potentially reducing the risk of injuries (120, 121).

However, our experience with PMSys athlete self-report measures at Alfheim, is that education and feedback must be part of the process, in order to maintain daily usage. It is of utmost importance that players clearly understand why these self-report measures are used, the purpose of the questions, who is analysing the data and that this data is used only for their benefit and not to their detriment. Finally, coaches should also keep a daily and interactive feedback process with the players in order to explain them which actions are taken in response to reported data.

## **5.5 Contextual analysis and methodological limitations**

According to some authors (4), researchers must consider the game context as a key factor when interpreting match physical outcomes. According to this perspective, other authors also defended that coaches should attempt to supplement training exercises with stimulus related to players' roles and principles of the club's playing style (111). A variety of factors, such as the

country's football culture, environmental conditions, club's style of play, etc., can be described as contextual dependent.

All our studies were performed with a Norwegian elite football club, using data from youth players (Paper 1), as well as from senior male (Papers 1, 2, 3, 4 and 5) and female athletes (Paper 1). Even though Norwegian football is well known from its particular style of play (direct play and with a high frequency of both offensive and defensive transitions), in Paper 3 (2017 season) we make it clear that the change of the head-coach also changed the club's philosophy to a much more complex way of play. A more possession and position-oriented style of play was adopted (1-3-5-2) instead of the more direct and counter-attack strategy used in the first half of the season (1-4-5-1). However, even with all these changes, the rest of the context remained the same (same players with similar physical capacities).

In relation to the effect of environmental conditions on player on-field performance, previous research (122) reported lower work-rates and distances covered at high intensities when the matches were played in warmer conditions (30 vs 20 degrees Celsius). The results showed that the distances covered in HIR were almost halved when playing at 30° (500 m) compared to a temperature of 20° (900 m). Even though, the reality of the environmental conditions experienced during our studies (with some matches, during the winter being played with temperatures below 0°C) is far from being the one presented in the study of Ekblom (122). His results show that environmental conditions can drastically affect the players' performance. However, more recent controlled laboratory studies have also investigated the effect of cold conditions in trained humans' performance (123, 124). The authors concluded that these conditions may provoke adverse physiological effects on the athletes and consequently reduced performance.

Therefore, future research should ideally attempt to describe the football specific context presented, when providing physical conditioning guidelines and match performance outcomes. Furthermore, practitioners should take these contextual specificities into account when comparing the present results with other research.

One limitation observed in Papers 2, 3 and 5 refers to the match-to-match variability. Previous studies have shown that match-to-match variability in performance variables of elite football players is high (61, 125, 126) and that future research based in match performance requires large sample sizes to identify true systematic changes in workload. In fact, the sample sizes of our studies (18 players/138 obs; 22 players/108 obs; 18 players/136 obs; for Papers 2, 3 and 5, respectively) might be of such small numbers that true differences can be masked due

to a statistical type 2 error, and such a consequence cannot be conclusively ruled out. In Paper 3, for instance, the results presented did not fully support the initial hypothesis established by the authors, probably because match-to-match variability was larger than the differences in physical performance between the two tactical systems analysed. Previous similar studies have analysed more matches (77) or used considerably larger sample sizes (42) than our study. However, others have not compared the physical demands of different tactical systems within the same players in the same context (same season and team) and to do so, a larger sample size than the one presented in our study becomes a difficult task to fulfil. Like most of the measures in team sports performance, the physical variables used in our studies are subject to a high variation between consecutive matches (125). In addition, previous studies have concluded that within-subject (player) and between-match variation in physical performance across the season might be experienced due to changes in the physical condition of the player (17, 127) and environmental conditions (122).

Even though, the methodology used to determine the team formations in Paper 2 and 3 is in line with previous studies (42, 55, 65, 77, 128, 129), the process of defining team formations and controlling their consistency throughout the matches was based on the subjective assessment of observers.

In Paper 1 we discuss the use of different tracking technologies and the readers must consider that the majority of research within the domain of this thesis has been made using GPS, while we used an LPM system. It should be noted that different measurement technologies could cause the discrepancy in results between our studies and previous research (18).

Due to the limitations of the tracking systems available to accurately quantify the goalkeepers' specific actions in matches and trainings, we decided not to include them in any of our studies. However, their match activity profiles could be useful and interesting to analyse and further research may attempt to develop a more efficient way of including goalkeepers in studies.

Moreover, in our studies, and in accordance with the literature (28, 29), the speed thresholds of HIR ( $>19.8 \text{ km}\cdot\text{h}^{-1}$ ) and sprints ( $>25.2 \text{ km}\cdot\text{h}^{-1}$ ) were set the same for every player with exception to the female players used in part of Paper 1, where they used a lower speed threshold for HIR ( $>16.0 \text{ km}\cdot\text{h}^{-1}$ ) and sprints ( $>20.0 \text{ km}\cdot\text{h}^{-1}$ ) (73). Some authors have, however, suggested the individualization of speed thresholds for external loads expressed relative to maximum speed of the player performed during speed tests (130). According to the authors, this type of individualized approach may benefit coaches when prescribing training programs, but will limit future comparisons with other studies using different teams and leagues.

Finally, one additional challenge experienced relates to the use of real-world (applied) research in our studies instead of pure basic research. With basic research, biases and contextual variables could be more efficiently controlled than with applied research. However, with this option (applied research) we were able to not only produce new knowledge, but also to solve specific problems presented in the football environment (131). This means that content of practices, tactical changes and types of periodization used, for instance, were the entire responsibility of coaches and the researchers needed to adapt to the circumstances of the training and matches. In sport science, both type of research (basic and applied) are useful and crucial to the development of the quality of training. However, we conjecture that with the use of applied research authors show interest to know what are the challenges and emergent issues among the different teams and which practical applications can be drawn in order to help practitioners in their daily work in clubs and federations.

The topic of real-world research comes in line with the idea that more research should include a user involvement/interaction. Even though we as researchers were not able to modify, by our own interest, the trainings and team tactics, the interaction with the coaches (users) was maintained during all the process. This interaction was accomplished through staff daily meetings, weekly reports delivered to coaches and players, etc. Therefore, positive influences were observed while the research was carried out, with adaptations of training drills and types of periodization being made when the studies' results were presented and discussed with the coaches. This way of interacting, apart from helping researchers with the studies' dissemination, also involves coaches and practitioners as part of the process, increasing their interest and willingness to collaborate in future projects. During the seasons 2018 and 2019, the author of this thesis has held the position as assistant coach of the team where the data was collected.

## **5.6 Project overview**

Figure 1 illustrates the links of the five Papers included in this thesis relative to each other. Papers 2, 3 and 5 were the core structure of the project, while Papers 1 and 4 were considered as supportive research, in order to strengthen the main studies.

Paper 1, which was used as a complementary study, describes the accuracy of the tracking system used and adds validity to all the following research. Paper 2 can be considered as the groundwork, where a descriptive approach was used and the thematic of position-specificity

raised. The positional differences observed in Paper 2 were therefore deeply analysed and compared (in Paper 3) between two different tactical formations. Then, Paper 3 appears as a causal relation of Paper 2 and its results. After presenting findings about the variation of position-specific player load in match-play, we aimed to transfer these insights into daily practice (training sessions and coaches' decisions). Consequently, with Paper 4 we presented solutions for a practical application of the performance data previously collected. At the same time, the research for Paper 5 was carried out in order to present some challenges and key-indicators that coaches might consider, when analysing training data, as well as to underline the importance of a better training individualization within the collective periodization.

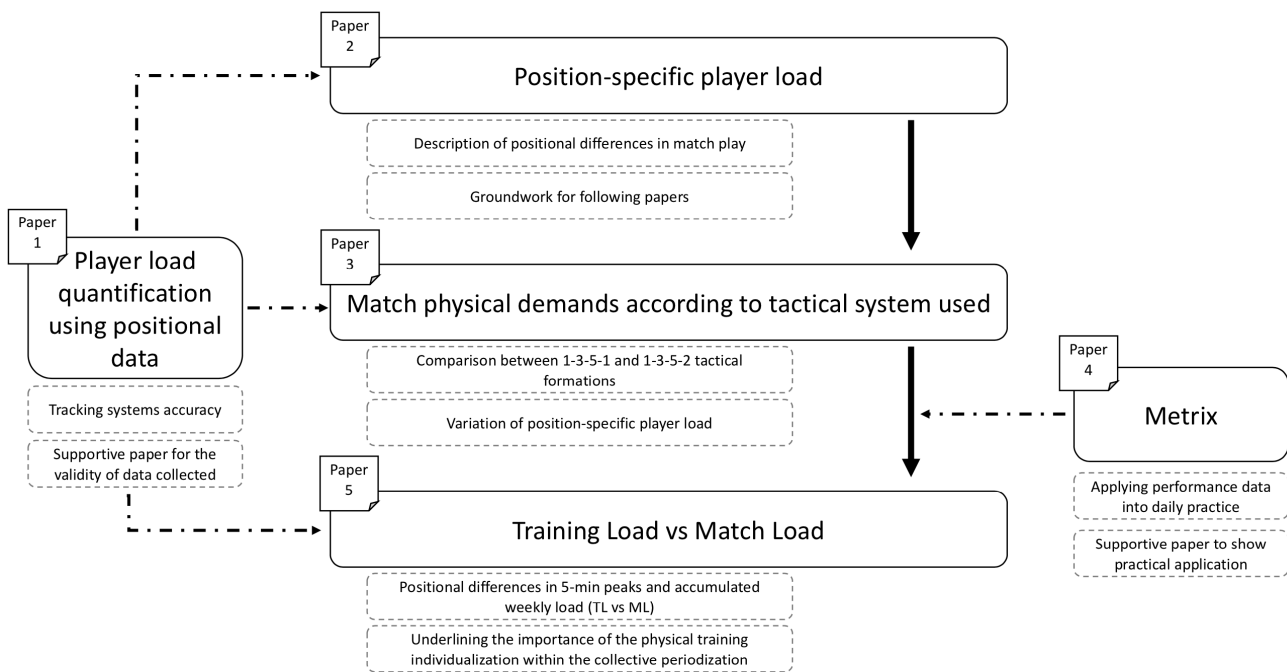


Figure 2. Project overview. Thesis pathway and connection between the five Papers included.

## 6 Conclusion

The overall aim of the thesis was to assess the different levels of specificity (similarity to match-play) that different playing-positions are subject to during training sessions in an elite football club. We hypothesized that: *different playing positions accumulate different relative training load compared to their match demands.*

### 6.1 Contribution

The first Paper described in this thesis, suggests that existing positional technologies do not ensure a complete and accurate measurement of player locomotor activities. In particular, the usefulness of GPS data is even more doubtful when small-sided games constitute a substantial part of the trainings. Such challenge occurs since the accurate quantification of short, but physically important, actions (e.g. acc and changes of direction) seem to be somewhat compromised. Therefore, complimenting GPS or LPM positional data with data from video and self-reporting tools, may help practitioners to improve players' performance and to better predict/avoid injuries. Furthermore, results shown in the subsequent Papers demonstrate that physical demands in official match-play, in elite football, vary greatly across playing position. Such differences were also proved to be, to a certain extent, related with the tactical system used and style of play adopted by the team/club. Finally, physical performance variables such as  $HIR_{dist}$ ,  $sprint_{dist}$  and  $sprint_{peak}$  seem to be neglected in trainings, when compared to the high frequency of acc and dec performed. Consequently, in order to prepare players of different playing positions to successfully perform their match demands, a higher level of training specificity is required. Creating training programs in order to add position-specific loads to the players, while adapting those drills according to the team's style of play, may be a solution to be followed by coaches and practitioners. Finally, in order to help coaches to solve these problems, we developed a toolkit (Metrix) that provides real-time analysis of each player's performance data, allowing them to analyse TL and act while the practices are ongoing.

### 6.2 Future research

This project and its studies, apart from contributing to the literature by providing new insights and practical applications, also identified some specific areas of research where information is still scarce and future research needed.

As previously mentioned, goalkeepers were not included in our studies and so, the match/training physical demands of this playing position remain unclear. The future development of tracking technology should attempt to upgrade their systems in order to accurately quantify the goalkeepers' specific football actions, such as jumps, dives, etc. Then, future research may use a similar methodology as in Paper 5, but including goalkeepers as one of the playing positions analysed.

Moreover, in our studies, team formations were subjectively defined which means that there is a clear opportunity for future research to improve our methodology by objectively defining team's tactical formation and its changes during the match. The use of positional data may help researchers to solve this challenge. In this particular case, we also suggest the measurement of the team's compactness (area occupied by the 10 outfield players) in match-play, so correlations with ML could be drawn.

Furthermore, one of the biggest limitations of the tracking system used is the fact that ball positioning is not provided. This means that the results presented in this research can be complemented by new insights if future studies efficiently manage to describe ball positioning in match-play (e.g. time spent with the ball on last-third, time spent with the ball on own half, time spent with/without ball possession, etc.).

Future research should also attempt to better contextualize TL, so practitioners can visualize the specific physical demands of different exercises. In general, a broader overview of the relation between TL and ML in professional football is needed, so effects of different periodization and methodological strategies can be spotted. In addition, TL associated with individual practices, non-starters additional training sessions and recovery sessions should be taken into consideration in order to provide information about the additional load these practices add to the players.

Finally, in order to replicate our studies and confirm our findings, we recommend researchers to attempt to use a larger cohort in future studies.



## References

1. Flanagan T. The measurement and analysis of the physical performance of soccer players: RMIT University; 2010.
2. Bradley P, Sheldon W, Wooster B, Olsen P, Boanas P, Krstrup P. High-intensity running in English FA Premier League soccer matches. *J Sports Sci.* 2009;27(2):159-68.
3. Osgnach C, Poser S, Bernardini R, Rinaldo R, di Prampero PE. Energy cost and metabolic power in elite soccer: a new match analysis approach. *Medicine and science in sports and exercise.* 2010;42(1):170-8.
4. Bradley P, Di Mascio M, Mohr M, Fransson D, Wells C, Moreira A, et al. Can modern football match demands be translated into novel training and testing modes? *Aspetar Sports Medicine Journal.* 2018;7:46-52.
5. Buchheit M, Simpson BM. Player-Tracking Technology: Half-Full or Half-Empty Glass? *International journal of sports physiology and performance.* 2017;12(Suppl 2):S235-s41.
6. Stevens TG, de Ruiter CJ, van Niel C, van de Rhee R, Beek PJ, Savelsbergh GJ. Measuring acceleration and deceleration in soccer-specific movements using a local position measurement (LPM) system. *International journal of sports physiology and performance.* 2014;9(3):446-56.
7. Pettersen SA, Johansen HD, Baptista IAM, Halvorsen P, Johansen D. Quantified Soccer Using Positional Data: A Case Study. *Frontiers in Physiology.* 2018;9(866).
8. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports medicine (Auckland, NZ).* 2014;44 Suppl 2:S139-47.
9. Impellizzeri FM, Rampinini E, Coutts AJ, Sassi A, Marcora SM. Use of RPE-based training load in soccer. *Medicine and science in sports and exercise.* 2004;36(6):1042-7.
10. Stevens TGA. External Load During Football Training. The power of acceleration and deceleration: Vrije Universiteit Amsterdam; 2017.
11. Wiik T, Johansen H, Pettersen S, Baptista I, Johansen D, Riegler M, et al. Predicting Peak Readiness-to-Train of Soccer Players Using Long Short-Term Memory Recurrent Neural Networks 2019.
12. Portas MD, Harley JA, Barnes CA, Rush CJ. 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.* 2010;5(4):448-58.
13. Rawstorn JC, Maddison R, Ali A, Foskett A, Gant N. Rapid Directional Change Degrades GPS Distance Measurement Validity during Intermittent Intensity Running. *PLOS ONE.* 2014;9(4):e93693.
14. Frencken WG, Lemmink KA, Delleman NJ. Soccer-specific accuracy and validity of the local position measurement (LPM) system. *J Sci Med Sport.* 2010;13(6):641-5.
15. Andersson H, Ekblom B, Krstrup P. Elite football on artificial turf versus natural grass: movement patterns, technical standards, and player impressions. *J Sports Sci.* 2008;26(2):113-22.
16. Mohr M, Krstrup P, Andersson H, Kirkendal D, Bangsbo J. Match activities of elite women soccer players at different performance levels. *J Strength Cond Res.* 2008;22(2):341-9.
17. Mohr M, Krstrup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci.* 2003;21(7):519-28.
18. Randers MB, Mujika I, Hewitt A, Santisteban J, Bischoff R, Solano R, et al. Application of four different football match analysis systems: a comparative study. *J Sports Sci.* 2010;28(2):171-82.
19. Bishop D, Spencer M, Duffield R, Lawrence S. The validity of a repeated sprint ability test. *J Sci Med Sport.* 2001;4(1):19-29.
20. Carling C, Dupont G. Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *J Sports Sci.* 2011;29(1):63-71.
21. Carling C, Le Gall F, Dupont G. Analysis of repeated high-intensity running performance in professional soccer. *J Sports Sci.* 2012;30(4):325-36.
22. Girard O, Mendez-Villanueva A, Bishop D. Repeated-sprint ability - part I: factors contributing to fatigue. *Sports medicine (Auckland, NZ).* 2011;41(8):673-94.

23. Bangsbo J. The physiology of soccer--with special reference to intense intermittent exercise. *Acta physiologica Scandinavica Supplementum*. 1994;619:1-155.
24. Drust B, Atkinson G, Reilly T. Future perspectives in the evaluation of the physiological demands of soccer. *Sports medicine (Auckland, NZ)*. 2007;37(9):783-805.
25. Mohr M, Krstrup P, Bangsbo J. Fatigue in soccer: a brief review. *J Sports Sci*. 2005;23(6):593-9.
26. Faude O, Koch T, Meyer T. Straight sprinting is the most frequent action in goal situations in professional football. *J Sports Sci*. 2012;30(7):625-31.
27. Rienzi E, Drust B, Reilly T, Carter JE, Martin A. Investigation of anthropometric and work-rate profiles of elite South American international soccer players. *The Journal of sports medicine and physical fitness*. 2000;40(2):162-9.
28. Dalen T, Ingebrigtsen J, Ettema G, Hjelde GH, Wisloff U. Player Load, Acceleration, and Deceleration During Forty-Five Competitive Matches of Elite Soccer. *J Strength Cond Res*. 2016;30(2):351-9.
29. Ingebrigtsen J, Dalen T, Hjelde GH, Drust B, Wisloff U. Acceleration and sprint profiles of a professional elite football team in match play. *Eur J Sport Sci*. 2015;15(2):101-10.
30. Bangsbo J, Norregaard L, Thorso F. Activity profile of competition soccer. *Canadian journal of sport sciences = Journal canadien des sciences du sport*. 1991;16(2):110-6.
31. Di Salvo V, Baron R, Tschan H, Calderon Montero FJ, Bachl N, Pigozzi F. Performance characteristics according to playing position in elite soccer. *Int J Sports Med*. 2007;28(3):222-7.
32. Krstrup P, Mohr M, Ellingsgaard H, Bangsbo J. Physical demands during an elite female soccer game: importance of training status. *Medicine and science in sports and exercise*. 2005;37(7):1242-8.
33. Bradley PS, Archer DT, Hogg B, Schuth G, Bush M, Carling C, et al. Tier-specific evolution of match performance characteristics in the English Premier League: it's getting tougher at the top. *J Sports Sci*. 2016;34(10):980-7.
34. Collet C. The possession game? A comparative analysis of ball retention and team success in European and international football, 2007-2010. *J Sports Sci*. 2013;31(2):123-36.
35. Paul DJ, Bradley PS, Nassis GP. Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *International journal of sports physiology and performance*. 2015;10(4):516-9.
36. Bradley P, Lago-Penas C, Rey E, Gomez Diaz A. The effect of high and low percentage ball possession on physical and technical profiles in English FA Premier League soccer matches. *J Sports Sci*. 2013;31(12):1261-70.
37. Di Salvo V, Pigozzi F, Gonzalez-Haro C, Laughlin MS, De Witt JK. Match performance comparison in top English soccer leagues. *Int J Sports Med*. 2013;34(6):526-32.
38. Bradley P, Carling C, Gomez Diaz A, Hood P, Barnes C, Ade J, et al. Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Human movement science*. 2013;32(4):808-21.
39. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri FM. Variation in top level soccer match performance. *Int J Sports Med*. 2007;28(12):1018-24.
40. Bloomfield J, Polman R, O'Donoghue P. Physical Demands of Different Positions in FA Premier League Soccer. *Journal of sports science & medicine*. 2007;6(1):63-70.
41. Schuth G, Carr G, Barnes C, Carling C, Bradley PS. Positional interchanges influence the physical and technical match performance variables of elite soccer players. *J Sports Sci*. 2016;34(6):501-8.
42. Bradley P, Carling C, Archer D, Roberts J, Dodds A, Di Mascio M, et al. The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *J Sports Sci*. 2011;29(8):821-30.
43. Moura FA, Martins LE, Anido Rde O, de Barros RM, Cunha SA. Quantitative analysis of Brazilian football players' organisation on the pitch. *Sports biomechanics*. 2012;11(1):85-96.
44. Rein R, Memmert D. Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus*. 2016;5(1):1410.
45. Sampaio J, Macas V. Measuring tactical behaviour in football. *Int J Sports Med*. 2012;33(5):395-401.

46. Sarmiento H, Marcelino R, Anguera MT, CampaniCo J, Matos N, LeitAo JC. Match analysis in football: a systematic review. *J Sports Sci.* 2014;32(20):1831-43.
47. Bartlett R, Button C, Robins M, Dutt-Mazumder A, Kennedy G. Analysing Team Coordination Patterns from Player Movement Trajectories in Soccer: Methodological Considerations. *International Journal of Performance Analysis in Sport International Journal of Performance Analysis in Sport.* 2017;12(2):398-424.
48. Moura FA, Martins LE, Anido RO, Ruffino PR, Barros RM, Cunha SA. A spectral analysis of team dynamics and tactics in Brazilian football. *J Sports Sci.* 2013;31(14):1568-77.
49. Bilge M. Game Analysis of Olympic, World and European Championships in Men's Handball. *J Hum Kinet.* 2012;35:109-18.
50. Haake SJ, Foster LI, James DM. An improvement index to quantify the evolution of performance in running. *J Sports Sci.* 2014;32(7):610-22.
51. Norton KI, Craig NP, Olds TS. The evolution of Australian football. *J Sci Med Sport.* 1999;2(4):389-404.
52. Woods CT, Robertson S, Collier NF, Swinbourne AL, Leicht AS. Transferring an Analytical Technique from Ecology to the Sport Sciences. *Sports medicine (Auckland, NZ).* 2018;48(3):725-32.
53. Bush M, Barnes C, Archer DT, Hogg B, Bradley PS. Evolution of match performance parameters for various playing positions in the English Premier League. *Human movement science.* 2015;39:1-11.
54. Barnes C, Archer DT, Hogg B, Bush M, Bradley PS. The evolution of physical and technical performance parameters in the English Premier League. *Int J Sports Med.* 2014;35(13):1095-100.
55. Aquino R, Carling C, Palucci Vieira LH, Martins G, Jabor G, Machado J, et al. Influence of Situational Variables, Team Formation, and Playing Position on Match Running Performance and Social Network Analysis in Brazilian Professional Soccer Players. *J Strength Cond Res.* 2018.
56. Baptista I, Johansen D, Seabra A, Pettersen SA. Position specific player load during match-play in a professional football club. *PLoS One.* 2018;13(5).
57. Martin-Garcia A, Casamichana D, Diaz AG, Cos F, Gabbett TJ. Positional Differences in the Most Demanding Passages of Play in Football Competition. *Journal of sports science & medicine.* 2018;17(4):563-70.
58. Akenhead R, Harley JA, Tweddle SP. Examining the External Training Load of an English Premier League Football Team With Special Reference to Acceleration. *J Strength Cond Res.* 2016;30(9):2424-32.
59. Bangsbo J. Energy demands in competitive soccer. *J Sports Sci.* 1994;12 Spec No:S5-12.
60. Bradley PS, Di Mascio M, Peart D, Olsen P, Sheldon B. High-intensity activity profiles of elite soccer players at different performance levels. *J Strength Cond Res.* 2010;24(9):2343-51.
61. Carling C, Bradley P, McCall A, Dupont G. Match-to-match variability in high-speed running activity in a professional soccer team. *J Sports Sci.* 2016;34(24):2215-23.
62. Clemente FM, Couceiro MS, Martins FM, Ivanova MO, Mendes R. Activity profiles of soccer players during the 2010 world cup. *J Hum Kinet.* 2013;38:201-11.
63. Gabbett TJ, Mulvey MJ. Time-motion analysis of small-sided training games and competition in elite women soccer players. *J Strength Cond Res.* 2008;22(2):543-52.
64. Gomez-Carmona CD, Gamonales JM, Pino-Ortega J, Ibanez SJ. Comparative Analysis of Load Profile between Small-Sided Games and Official Matches in Youth Soccer Players. *Sports (Basel, Switzerland).* 2018;6(4).
65. Lacombe M, Simpson BM, Cholley Y, Lambert P, Buchheit M. Small-Sided Games in Elite Soccer: Does One Size Fit All? *International journal of sports physiology and performance.* 2018;13(5):568-76.
66. Ade J, Fitzpatrick J, Bradley PS. High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. *J Sports Sci.* 2016;34(24):2205-14.
67. Small K, McNaughton L, Greig M, Lovell R. Effect of timing of eccentric hamstring strengthening exercises during soccer training: implications for muscle fatigability. *J Strength Cond Res.* 2009;23(4):1077-83.
68. Lakshman M, Sinha L, Biswas M, Charles M, Arora NK. Quantitative vs qualitative research methods. *Indian J Pediatr.* 2000;67(5):369-77.

69. Winter EM, Maughan RJ. Requirements for ethics approvals. *J Sports Sci.* 2009;27(10):985.
70. Commission E. Open innovation, open science, open to the world - a vision for Europe 2016 [Available from: <https://ec.europa.eu/digital-single-market/en/news/open-innovation-open-science-open-world-vision-europe>].
71. Commission E. Horizon 2020 2019 [Available from: [https://ec.europa.eu/research/participants/data/ref/h2020/wp/2018-2020/main/h2020-wp1820-swfs\\_en.pdf](https://ec.europa.eu/research/participants/data/ref/h2020/wp/2018-2020/main/h2020-wp1820-swfs_en.pdf)].
72. Commission E. Data management [Available from: [https://ec.europa.eu/research/participants/docs/h2020-funding-guide/cross-cutting-issues/open-access-data-management/data-management\\_en.htm](https://ec.europa.eu/research/participants/docs/h2020-funding-guide/cross-cutting-issues/open-access-data-management/data-management_en.htm)].
73. Bendiksen M, Pettersen SA, Ingebrigtsen J, Randers MB, Brito J, Mohr M, et al. Application of the Copenhagen Soccer Test in high-level women players - locomotor activities, physiological response and sprint performance. *Human movement science.* 2013;32(6):1430-42.
74. Schimpchen J, Skorski S, Nopp S, Meyer T. Are "classical" tests of repeated-sprint ability in football externally valid? A new approach to determine in-game sprinting behaviour in elite football players. *J Sports Sci.* 2016;34(6):519-26.
75. Andersen TB, Krstrup P, Bendiksen M, Orntoft CO, Randers MB, Pettersen SA. Kicking Velocity and Effect on Match Performance When using a Smaller, Lighter Ball in Women's Football. *Int J Sports Med.* 2016;37(12):966-72.
76. Cohen J. *Statistical Power Analysis for the Behavioral Sciences.* 2nd ed. Hillsdale, NJ: Lawrence Earlbaum Associate; 1988.
77. Carling C. Influence of opposition team formation on physical and skill-related performance in a professional soccer team. *European Journal of Sport Science.* 2011;11(3):155-64.
78. Rosnow RL, Rosenthal R, Rubin DB. Contrasts and correlations in effect-size estimation. *Psychological science.* 2000;11(6):446-53.
79. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Medicine and science in sports and exercise.* 2009;41(1):3-13.
80. Denning PJ, Comer DE, Gries D, Mulder MC, Tucker A, Turner AJ, et al. Report of the ACM Task Force on The Core of Computer Science. ACM; 1988. Report No.: 0-8791-293-4.
81. Stensland HK, Gaddam VR, Tennøe M, Helgedagsrud E, Næss M, Alstad HK, et al. Bagadus: An integrated real-time system for soccer analytics. *ACM Trans Multimedia Comput Commun Appl.* 2014;10(1s):1-21.
82. Stevens TGA, de Ruyter CJ, Twisk JWR, Savelsbergh GJP, Beek PJ. Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players. *Science and Medicine in Football.* 2017;1(2):117-25.
83. Clemente FM, Rabbani A, Conte D, Castillo D, Afonso J, Truman Clark CC, et al. Training/Match External Load Ratios in Professional Soccer Players: A Full-Season Study. *Int J Environ Res Public Health.* 2019;16(17).
84. Krstrup P, Mohr M, Amstrup T, Rysgaard T, Johansen J, Steensberg A, et al. The yo-yo intermittent recovery test: physiological response, reliability, and validity. *Medicine and science in sports and exercise.* 2003;35(4):697-705.
85. Team RC. A Language and Environment for Statistical Computing R Foundation for Statistical Computing, Vienna, Austria 2019 [Available from: <http://www.R-project.org/>].
86. Aughey RJ. Australian football player work rate: evidence of fatigue and pacing? *International journal of sports physiology and performance.* 2010;5(3):394-405.
87. Johansen HD, Pettersem SA, Halvorsen P, Johansen D, editors. Combining video and player telemetry for evidence-based decisions in soccer. Proceedings of the International Congress on Sports Science Research and Technology Support (icSport) (INSTICC); 2013; Algarve.
88. Buchheit M, Al Haddad H, Simpson BM, Palazzi D, Bourdon PC, Di Salvo V, et al. Monitoring accelerations with GPS in football: time to slow down? *International journal of sports physiology and performance.* 2014;9(3):442-5.
89. Langley RB. Dilution of Precision. *GPS World* (1999). p. 52 - 9.
90. Castellano J, Casamichana D, Calleja-Gonzalez J, Roman JS, Ostojic SM. Reliability and Accuracy of 10 Hz GPS Devices for Short-Distance Exercise. *Journal of sports science & medicine.* 2011;10(1):233-4.

91. Jennings D, Cormack S, Coutts AJ, Boyd LJ, Aughey RJ. Variability of GPS units for measuring distance in team sport movements. *International journal of sports physiology and performance*. 2010;5(4):565-9.
92. Di Mascio M, Bradley PS. Evaluation of the most intense high-intensity running period in English FA premier league soccer matches. *J Strength Cond Res*. 2013;27(4):909-15.
93. Aughey RJ, Varley MC. Acceleration profiles in elite Australian soccer. *Int J Sports Med*. 2013;34(3):282.
94. Di Salvo V, Baron R, Gonzalez-Haro C, Gormasz C, Pigozzi F, Bachl N. Sprinting analysis of elite soccer players during European Champions League and UEFA Cup matches. *J Sports Sci*. 2010;28(14):1489-94.
95. Bangsbo J, Mohr M. Variations in Running Speeds and Recovery Time After a Sprint During Top-class Soccer Matches. *Medicine and science in sports and exercise*. 2005;37(5).
96. Bangsbo J, Peitersen B. Soccer systems and strategies. Champaign IL: Human Kinetics; 2000.
97. Lago C. The influence of match location, quality of opposition, and match status on possession strategies in professional association football. *J Sports Sci*. 2009;27(13):1463-9.
98. Castellano J, Blanco-Villasenor A, Alvarez D. Contextual variables and time-motion analysis in soccer. *Int J Sports Med*. 2011;32(6):415-21.
99. Lago-Penas C, Dellal A. Ball possession strategies in elite soccer according to the evolution of the match-score: the influence of situational variables. *J Hum Kinet*. 2010;25:93-100.
100. Redwood-Brown AJ, O'Donoghue PG, Nevill AM, Seward C, Dyer N, Sunderland C. Effects of situational variables on the physical activity profiles of elite soccer players in different score line states. *Scand J Med Sci Sports*. 2018.
101. Rebelo AN, Silva P, Rago V, Barreira D, Krstrup P. Differences in strength and speed demands between 4v4 and 8v8 small-sided football games. *J Sports Sci*. 2016;34(24):2246-54.
102. Hodgson C, Akenhead R, Thomas K. Time-motion analysis of acceleration demands of 4v4 small-sided soccer games played on different pitch sizes. *Human movement science*. 2014;33:25-32.
103. Gaudino P, Iaia FM, Alberti G, Strudwick AJ, Atkinson G, Gregson W. Monitoring training in elite soccer players: systematic bias between running speed and metabolic power data. *Int J Sports Med*. 2013;34(11):963-8.
104. Gabbett TJ. Influence of training and match intensity on injuries in rugby league. *J Sports Sci*. 2004;22(5):409-17.
105. Rogalski B, Dawson B, Heasman J, Gabbett TJ. Training and game loads and injury risk in elite Australian footballers. *J Sci Med Sport*. 2013;16(6):499-503.
106. Higham DG, Pyne DB, Anson JM, Hopkins WG, Eddy A. Comparison of Activity Profiles and Physiological Demands Between International Rugby Sevens Matches and Training. *J Strength Cond Res*. 2016;30(5):1287-94.
107. Akenhead R, French D, Thompson KG, Hayes PR. The physiological consequences of acceleration during shuttle running. *Int J Sports Med*. 2015;36(4):302-7.
108. Mero A, Komi PV. Force-, EMG-, and elasticity-velocity relationships at submaximal, maximal and supramaximal running speeds in sprinters. *Eur J Appl Physiol Occup Physiol*. 1986;55(5):553-61.
109. Mero A, Komi PV. Electromyographic activity in sprinting at speeds ranging from sub-maximal to supra-maximal. *Medicine and science in sports and exercise*. 1987;19(3):266-74.
110. Stevens TG, De Ruiter CJ, Van Maurik D, Van Lierop CJ, Savelsbergh GJ, Beek PJ. Measured and estimated energy cost of constant and shuttle running in soccer players. *Medicine and science in sports and exercise*. 2015;47(6):1219-24.
111. Bradley P, Martin-Garcia A, Ade J, Diaz A. POSITION SPECIFIC AND POSITIONAL PLAY TRAINING IN ELITE FOOTBALL: CONTEXT MATTERS (Barca Innovation Hub Overview). 2019.
112. Carling C, Williams AM, Reilly T. Handbook of Soccer Match Analysis: A Systematic Approach to Improving Performance. *Journal of sports science & medicine*. 2006;5(1):171-.
113. Gaddam VR, Eg R, Langseth R, Griwodz C, #229, Halvorsen I. The Cameraman Operating My Virtual Camera is Artificial: Can the Machine Be as Good as a Human&quest. *ACM Trans Multimedia Comput Commun Appl*. 2015;11(4):1-20.

114. Gaddam VR, Langseth R, #229, Stensland kK, Gurdjos P, Charvillat V, et al. Be your own cameraman: real-time support for zooming and panning into stored and live panoramic video. *Proceedings of the 5th ACM Multimedia Systems Conference*; Singapore, Singapore. 2579370: ACM; 2014. p. 168-71.
115. Mortensen A, Gaddam VR, #229, Stensland kK, Griwodz C, Johansen D, et al. Automatic event extraction and video summaries from soccer games. *Proceedings of the 5th ACM Multimedia Systems Conference*; Singapore, Singapore. 2579374: ACM; 2014. p. 176-9.
116. Johansen D, Stenhaus M, Hansen RBA, Christensen A, Høgmo PM, editors. Muithu: smaller footprint potentially larger imprint. *Proceedings of IEEE ICDIM*; 2012; Algarve.
117. Oliveira R, Brito JP, Martins A, Mendes B, Marinho DA, Ferraz R, et al. In-season internal and external training load quantification of an elite European soccer team. *PLoS One*. 2019;14(4):e0209393.
118. Noor D, McCall A, Jones M, Duncan C, Ehrmann F, Meyer T, et al. Transitioning from club to national teams: Training and match load profiles of international footballers. *J Sci Med Sport*. 2019;22(8):948-54.
119. Clemente FM. Associations between wellness and internal and external load variables in two intermittent small-sided soccer games. *Physiol Behav*. 2018;197:9-14.
120. Jaspers A, De Beeck TO, Brink MS, Frencken WGP, Staes F, Davis JJ, et al. Predicting Future Perceived Wellness in Professional Soccer: The Role of Preceding Load and Wellness. *International journal of sports physiology and performance*. 2019:1-25.
121. Lathlean TJH, Gatin PB, Newstead SV, Finch CF. A Prospective Cohort Study of Load and Wellness (Sleep, Fatigue, Soreness, Stress, and Mood) in Elite Junior Australian Football Players. *International journal of sports physiology and performance*. 2019:1-12.
122. Ekblom B. Applied physiology of soccer. *Sports medicine (Auckland, NZ)*. 1986;3(1):50-60.
123. Crowe MJ, O'Connor D, Rudd D. Cold water recovery reduces anaerobic performance. *Int J Sports Med*. 2007;28(12):994-8.
124. Tikuisis P, Ducharme MB, Moroz D, Jacobs I. Physiological responses of exercised-fatigued individuals exposed to wet-cold conditions. *J Appl Physiol (1985)*. 1999;86(4):1319-28.
125. Gregson W, Drust B, Atkinson G, Salvo VD. Match-to-match variability of high-speed activities in premier league soccer. *Int J Sports Med*. 2010;31(4):237-42.
126. Trewin J, Meylan C, Varley MC, Cronin J. The match-to-match variation of match-running in elite female soccer. *J Sci Med Sport*. 2018;21(2):196-201.
127. Krustup P, Bangsbo J. Physiological demands of top-class soccer refereeing in relation to physical capacity: effect of intense intermittent exercise training. *J Sports Sci*. 2001;19(11):881-91.
128. Baptista J, Travassos B, Goncalves B, Mourao P, Viana JL, Sampaio J. Exploring the effects of playing formations on tactical behaviour and external workload during football small-sided games. *J Strength Cond Res*. 2018.
129. Silva P, Chung D, Carvalho T, Cardoso T, Davids K, Araujo D, et al. Practice effects on intra-team synergies in football teams. *Human movement science*. 2016;46:39-51.
130. Sweeting AJ, Cormack SJ, Morgan S, Aughey RJ. When Is a Sprint a Sprint? A Review of the Analysis of Team-Sport Athlete Activity Profile. *Front Physiol*. 2017;8:432.
131. Ziman J. Is science losing its objectivity? *Nature*. 1996;382(6594):751-4.

# Paper 1



# Quantified Soccer Using Positional Data: A Case Study

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Performance development in international soccer is undergoing a silent revolution fueled by the rapidly increasing availability of athlete quantification data and advanced analytics. Objective performance data from teams and individual players are increasingly being collected automatically during practices and more recently also in matches after FIFA's 2015 approval of wearables in electronic performance and tracking systems. Some clubs have even started collecting data from players outside of the sport arenas. Further algorithmic analysis of these data might provide vital insights for individual training personalization and injury prevention, and also provide a foundation for evidence-based decisions for team performance improvements. This paper presents our experiences from using a detailed radio-based wearable positioning data system in an elite soccer club. We demonstrate how such a system can detect and find anomalies, trends, and insights vital for individual athletic and soccer team performance development. As an example, during a normal microcycle (6 days) full backs only covered 26% of the sprint distance they covered in the next match. This indicates that practitioners must carefully consider to proximity size and physical work pattern in microcycles to better resemble match performance. We also compare and discuss the accuracy between radio waves and GPS in sampling tracking data. Finally, we present how we are extending the radio-based positional system with a novel soccer analytics annotation system, and a real-time video processing system using a video camera array. This provides a novel toolkit for modern forward-looking soccer coaches that we hope to integrate in future studies.

**Keywords:** player load, athlete quantification, GPS tracking, LPM tracking, wearables, player monitoring

## 1. INTRODUCTION

Over the last decade, we have witnessed the emergence of a myriad of wearable devices and sensors for quantification of sport and physical activity. These are frequently touted as a game changer and a key for future development of many sports. Key sport governance organizations like Fédération Internationale de Football Association (FIFA), with its 265 million members in various local clubs world-wide (Kunz, 2007), have already approved use of wearables and Electronic Performance and Tracking Systems (EPTs) in official matches. This has undoubtedly accelerated research and development of athlete quantification technology. Training and matches are already being impacted. For instance, it is believed that the German national soccer team used wearable technology to profile the players, and with these statistics, coach Joachim Low made the crucial substitute of Mario Götze who scored the winning goal in the world cup final in Brazil 2014.



Although such success stories certainly do exist, the general usefulness of athlete quantification technologies has several shortcomings. The aim of this paper is to highlight some of the challenges we encountered when using positional data as part of research and team development, and to suggest other promising data sources. Our main observation is that athlete quantification systems are often inhibited by questionable validity of acquired data. We argue that by combining data from multiple systems, some of the shortcomings of existing positional tracking systems can be detected and perhaps avoided. All data in this report was collected from autumn 2011 until spring 2017. All participants have given their written informed consent, and the project has been given institutional approval.

## 2. TRACKING USING LPM (RADIO SIGNALS) AND GPS IN A PROFESSIONAL FOOTBALL CLUB

Football is an open-loop sport, and it is important to emphasize the need for more research to develop our understanding of valid indications of physical match performance and competitive success (Carling, 2013). Toward that end, the athlete quantification technologies deployed in our research facilities at Alfheim Stadium is already generating important insight. At Alfheim Stadium, there has been a substantial development and use of various tracking technology, including multiple camera semi-automatic systems, Local Position Measurement (LPM) systems, and GPS systems, each capable of quickly recording and storing data about team players. We have to a large extent moved away from GPS based technology, which has traditionally been the preferred choice by clubs to quantify training load of team-sports athletes, both during training and matches (Aughey, 2010).

An alternative to GPS based systems, are those based on LPM radio signals. Unlike GPS systems, where devices are passive receivers of signals from overhead satellites, LPM systems work by having the wearable emit signals to local receivers, which do the actual triangulation. Our experience is that LPM systems have better accuracy than GPS-based systems. In our case, we have several years of experience with positional tracking using the stationary LPM system: ZXY Sport Tracking System by ChyronHego (Trondheim, Norway). This system is based on using the 5.0 GHz Industrial, Scientific, and Medical (ISM) radio band for communication and signal transmissions. With ZXY, each player wears a belt with a transponder placed at his lumbar (Pettersen et al., 2014), and there are six stationary sensors placed at the stadium perimeter. The stationary sensors compute the position data for each belt by advanced vector based processing of the received radio signals. The processing system in each stationary sensor enables direct projection of the player's positions on the field without having to exchange data with other sensors. Multiple receivers are still required to cover the entire field and to avoid occlusions. The default resolution is fixed to 20 Hz for each belt. Data is stored in the system's internal database and can be exported as comma separated values files.

To quantify the accuracy difference of GPS technology compared to LPM systems, we performed two studies, as will be described next.

### 2.1. Study 1 and Study 2: GPS vs. LPM-Tracking

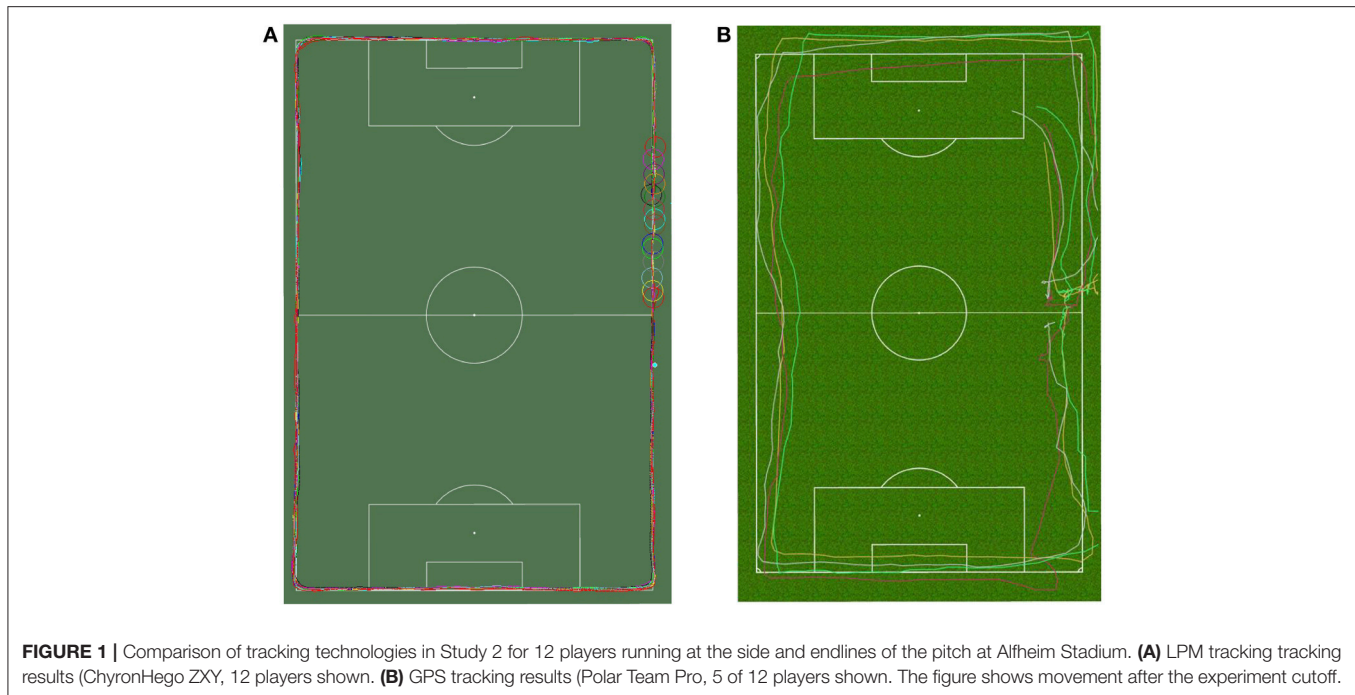
In Study 1 (2011), we instrumented 6 high-level female players (weight  $59.6 \pm 6.8$  kg, height  $171.5 \pm 4.2$  cm) with both GPS and LPM tags and instructed them to perform the Copenhagen Soccer Test for Women (CSTw). Each player ran the CSTw course 18 times, simulating a match and accumulating a distance of 10,331 m (Bendiksen et al., 2013). Each player wore two GPS tags from the GPSport SPI-ProX1 5.0 Hz system in a vest on their upper body, and two ZXY tags placed in a small belt near the lumbar spine. Having multiple tags enables us to measure both the inter and the intra reliability of the systems.

The average distance covered was measured by SPI-ProX1 (12 tags on 6 players) to  $11,668 \pm 1,072$  m with a CV value of 6%, while ZXY (14 tags on 7 players) measured the distance to  $10,204 \pm 103$  m with a CV value of 1%. For High Intensity Runs (HIRs) ( $>16.0$  km h<sup>-1</sup>), the values were  $612 \pm 433$  m with a CV value of 37.4% and  $1238 \pm 38$  m with a CV value of 3.1%, respectively.

In the intra reliability test, the measured discrepancy between the two tags placed on the same player ranged between 800 and 2,071 m using SPI-ProX1 and 25–290 m using ZXY. Our observation that the SPI-ProX1 system seems to measure higher values for total distance covered is further supported by an experiment where 19 players of two junior elite teams were equipped with both ZXY and SPI-ProX1. The average distance covered was measured by SPI-ProX1 to  $10,805 \pm 847$  m, while ZXY measured the distance to  $9,891 \pm 974$  m (Johansen et al., 2013).

In Study 2 (2016), 12 male youth elite players (weight  $64.2 \pm 8.2$  kg, height  $176.0 \pm 6.7$  cm) were instructed to jog clockwise around the pitch at Alfheim Stadium, following the side and end-lines of the pitch. All players wore both the Polar Team Pro 10 GHz GPS system (Kempele, Finland) and the ZXY system. The GPS tags were connected to the anterior part of the chest by an elastic chest strap. **Figure 1B** shows the recorded positional information for both Polar and ZXY. (The Polar system could not plot more than five players per figure.) As can be seen in the figures, players were not capable of performing 90° turns in the corners, which is to be expected. The GPS tracks in **Figure 1B** can clearly be seen to deviate significantly from the actual trajectory of the players, while the tracks shown in **Figure 1A** much more closely follow the lines. A similar effect was also observed by Buchheit et al. (2014).

Next, seven of the twelve players were selected to complete a training session. With statistical significance levels obtained by Paired *T*-test, sprint performance ( $>25.2$  km h<sup>-1</sup>) was measured lower by ZXY  $55.3 \pm 7.3$  m compared to Polar Team Pro  $70.0 \pm 12.9$  m ( $P > 0.05$ ). HIR and number of accelerations ( $\geq 2$  m s<sup>-2</sup>) showed an inverse tendency with higher values  $222.8 \pm 77.8$  m and  $100.9 \pm 19.9$  counts vs.  $164.4 \pm 54.9$  m and  $81.0 \pm 15.9$  counts (ns). All tracking generated raw data was



loaded into Microsoft Excel, where statistical procedures were executed.

It could be speculated that the GPS signal reception at Alfheim Stadium is poor. However, the stadium does not have an overhanging roof, nor are there any nearby high buildings that obscures the sky. A few 9 m high stands are located 9.3 m behind the sidelines, but we do not suspect these to interfere with the GPS signal. Measurement accuracy may still be reduced by atmospheric conditions such as clouds and fog. A more plausible explanation is perhaps the stadium's arctic location at 69.65° north. The inclination of GPS satellite orbits is approximately 55° (north or south), so that no satellites have been directly overhead during our tracking sessions (Langley, 1999). High error rates have, however, been reported elsewhere for inter-unit reliability across different GPS models (Jennings et al., 2010; Castellano et al., 2011). A stationary reference GPS receiver can improve accuracy by averaging its position over time. As long as such a reference receiver detects the same satellite signals as the wearable GPS receiver, it can send correction data. In the northern areas, GPS based solutions that also communicate with the Russian Global Navigation Satellite System (GLONASS) system should also be considered as these generally provide better precision here. Still, ours and Stevens et al. (2014) findings indicate superior accuracy in Local Position Systems (LPS) compared to GPS. It remains unclear to what extent the inherent accuracy limitation in the GPS system limits its usefulness for athlete quantification.

Although the CSTw has a 10,331 m preset course that the players should follow, some discrepancies in the measured distance are to be expected. Even small deviation of the sensor device from the set trajectories of the test, like the player leaning in the turns of the course, will impact the measurements and adds up throughout the test. However, the high meter values in

relation to the course length and in addition the large CV between units of the SPI-ProX1 system suggest that the results should be interpreted with caution.

Using an absolute sprinting or high-velocity threshold for all athletes in a team does not account for individual genetic or physiological differences. The same external load calculated by an acceleration, HIR, or sprinting threshold for two athletes could represent a different internal load based on individual characteristics (Impellizzeri et al., 2004). Positive and negative accelerations are metabolically demanding and often do not elicit velocities defined as HIR or sprint (Osgnach et al., 2010). The starting velocity is critical when measuring accelerations or decelerations, the metabolic cost of changing speed more than  $2.0 \text{ m s}^{-2}$  is much larger at a starting speed of  $5.0 \text{ m s}^{-1}$  compared to  $1.0 \text{ m s}^{-1}$ . In addition, quantification of these variables is dependent upon the validity and reliability of athlete tracking systems.

An alternative may be individual thresholds for external load expressed relative to maximum speed attained during sprint testing. An individualized approach of arbitrarily derived velocity thresholds may benefit the training prescription for players, but will limit comparisons with other teams and leagues. Limited research exists on how to individualize accelerations, which are energy demanding, and therefore, we will have limited information on total external load even with individualized speed zone limits (Sweeting et al., 2017).

## 2.2. Study 3: High Intensity Activity in Training vs. Match

In Study 3 (2017), 5 players (age  $25.2 \pm 4.0$ , height  $178.4 \pm 5.0 \text{ cm}$ , weight  $75.2 \pm 6.6 \text{ kg}$ ) were randomly selected from 5 different playing positions: central back, full back,

**TABLE 1 |** High-intensity actions (HIRs and Sprints) and number of appearances (counts) and/or meters for five training sessions, compared to an official match in five players in different positions.

	High Intensity Runs (HIRs)						Sprints					
	Count		%	Dist (m)		%	Count		%	Dist (m)		%
	Match	Train.	Match	Match	Train.	Match	Match	Train.	Match	Match	Train.	Match
CB	35	38	109	560	327	59	8	7	88	112	58	52
FB	44	54	123	835	694	83	13	11	85	183	104	57
CM	60	56	93	1305	698	53	16	4	25	259	67	26
WM	49	60	122	1032	559	54	18	10	56	228	84	37
CF	49	54	110	851	705	83	10	15	150	103	153	149

CB, Center back; FB, Full back; CM, Center midfield; WM, Wide midfielder; CF, Center forward.

The difference (% match) correspond to the total value of the training week compared to the match. The value of the match is considered as 100%. Example from a normal microcycle (5 training sessions between two official matches).

central midfielder, wide midfielder, and central forward. The players were tracked in 5 consecutive in-season training sessions (microcycle) and in one official home match. Distances and number of HIR and sprints were compared (Table 1). We observed large discrepancies in high-intensity activities between trainings in the microcycle and match. As shown in Table 1, we have recorded substantial underload in HIR and sprint for most players during the training week compared to match. Following the principle of overload, this indicates that the format of the small side games does not elicit the sufficient amount of HIR and sprint, with exception of the central forward position in the team’s style of play. Practitioners should be aware of and take into consideration how different pitch size and number of players dictate the external and internal training load.

From a training load perspective, the large intra/inter unit differences in tracked distance described in section 2 can also have significant practical implications for an athlete across a longitudinal period, which questions meaningful interpretation of the data. For within-athlete longitudinal monitoring, we therefore recommended that practitioners assign a specific device to each athlete. To appropriately detect changes in physical performance, researchers must also account for match-to-match variation and device reliability. Any possible interference between co-located devices has to our knowledge not yet been fully explored. Nevertheless, developing a device including algorithms describing position-specific match demands might be useful to control training load in relation to match demands. By integrating information about training content, load periodization, and fatigue status we can provide real-world insight into optimal approaches for player preparation.

### 3. PERSPECTIVE

The studies described above indicate that existing positional technologies do not guarantee an accurate measurement of player locomotor activities. We are therefore experimenting with two specific supplemental data sources that we plan to integrate in future studies: one based on video and one based on self-reporting.

### 3.1. Full-Stadium Video Coverage

Video of player actions are generally considered a useful tool for soccer analytics. Videos have traditionally been obtained from the following three sources: professional TV broadcasts, hand-held cameras, or fixed arena cameras. Unfortunately, these sources are either not available for practices, too personnel demanding, or too costly. More importantly, none of these solutions provide a sufficient high-resolution coverage of all players throughout a session. Our solution was to develop the Bagadus (Stensland et al., 2014) video system.

Bagadus consists of multiple small shutter and exposure synchronized cameras that record a high-resolution video of the soccer field. The cameras are set in a circular pattern; pitched, yawed, and rolled to look directly through a point five cm in front of the lenses, minimizing the parallax effect. Combined, the cameras cover the full pitch with sufficient overlap to identify common features necessary for camera calibration and image stitching to generate a panorama video.

Bagadus video playback can switch between streams delivered from the different cameras, either manually by selecting a camera, or automatically following players based on sensor information. It can also play back a panorama video stitched from the different camera feeds. Using the panorama video, a virtual view can also be extracted (Gaddam et al., 2015), for instance to automatically follow one particular player (Gaddam et al., 2014).

### 3.2. Video Indexing With Rich Metadata

Many elite soccer clubs spend much time on manual labor-intensive post-game analysis by carefully watching full-length recordings of the game. By enriching video archives with time-synchronized metadata from external sensors, Bagadus enables a much more efficient video retrieval and summarizing experience, reducing the time needed for coaches to locate relevant video segments. At Alfheim Stadium we found positional data from ZXY particularly useful as it enables Bagadus to track individual players and generate on-the-fly video summaries based on player or group formation and trajectories. For instance, a video summary of all situations where a particular player sprints toward

his own goal, or all situations where the midfielder is in the mid-circle (Mortensen et al., 2014).

In addition to positional data, we have developed an annotation system (Johansen et al., 2012; Stensland et al., 2014) for use *during* matches to tag important events with metadata as they occur. A key design principle for this system was minimizing deployment effort and hardware investments. Mobile devices like smartphones and tablets are as such ideal platforms as they are highly available, mostly Internet connected, and provide sufficient computational resources. In combination with an tile-based interface optimized for fast input, the average annotation time was cut down to less than 3 seconds (Johansen et al., 2012) while operated on the field. The registered events are time-aligned with the video and stored in an analytic database, immediately available for use by the video retrieval system. This enable video-based team or individual feedback in the locker room during half time, or after practice.

### 3.3. Individual Subjective Reports

We have also implemented a player monitoring system PMSys: a self-reporting system<sup>1</sup> for mobile devices, which enables monitoring of individual phenotypic parameters through repeated questionnaires that the players answer on their own mobile phones.

Having regular reports from all team members is a key goal for PMSys. As such, a key design requirement was support on all smart-phone platforms (e.g., iOS and Andoid) in use by team members. To reduce the costs of multi-platform support, we opted to develop PMSys as a hybrid-mobile application based on the Ionic 2+ Framework<sup>2</sup>. Recent versions of the framework generate applications that look and feel similar to native ones, and earlier performance and appearance disadvantages are mostly mitigated. PMSys is currently deployed in Google Play for Android devices, and in Apple's iTunes store for iOS devices. The mobile application provides graphical visualization feedback, which gives the player a timeline overview.

In addition to the smart-phone app, we also constructed a web-portal that team coaches can use to analyze and present data. The portal is constructed with the coaches in mind, providing several tools and plots for teams and individual players. In combination with the web portal and mobile application, we have implemented our own communication service between the mobile phone and the web portal, allowing a coach to send

push-messages directly to a player's mobile phone. A key feature of PMSys is the ability for coaches to schedule future and repeated push-messages.

Our experience with PMSys Athlete Self-Report Measures (ASRM) at Alfheim, is that education and feedback is of utmost importance to maintain daily usage. The scope of education should include why an ASRM should be used, the purpose of the questions asked, and who is analysing the data. Education should emphasize that results are to be used for the player benefit, and not to their detriment. Feedback should consist of daily interactions and reminders pushed directly to the users device, showing what action is taken in response to reported data. During the season, the generated daily wellness reports may form the basis of the regular conversations between coaching staff and players. Engagement of staff, especially in the implementation process, is essential (Saw et al., 2015), with particular emphasis on the need for a key-staff member to oversee the day-to-day responses and be able to analyze and interpret the ASRM.

By complimenting GPS and LPM positional data, like the ones we have used in our previous studies, with data from video and self-reporting tools, we hope to better predict injury or reduced performance for a player. The extended data sources are in particular interesting when considered as additional input to modern machine learning algorithms.

### ETHICS STATEMENT

The study is approved by the Norwegian Centre for Research Data and the players have given their written informed consent to participate.

### AUTHOR CONTRIBUTIONS

SP: data collection, in charge of the writing process; HJ, IB, PH, and DJ: data collection, manuscript writing.

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<sup>1</sup>PMSys, <http://forzasys.com/pmsys.html>.

<sup>2</sup><https://ionicframework.com/>

### REFERENCES

- Aughey, R. J. (2010). Australian football player work rate: evidence of fatigue and pacing? *Int. J. Sports Physiol. Perform.* 5, 394–405. doi: 10.1123/ijpspp.5.3.394
- Bendiksen, M., Pettersen, S. A., Ingebrigtsen, J., Randers, M. B., Brito, J., Mohr, M., et al. (2013). Application of the copenhagen soccer test in high-level women players locomotor activities, physiological response and sprint performance. *Hum. Mov. Sci.* 32, 1430–1442. doi: 10.1016/j.humov.2013.07.011

- Buchheit, M., Haddad, H. A., Simpson, B. M., Palazzi, D., Bourdon, P. C., Salvo, V. D., et al. (2014). Monitoring accelerations with GPS in football: time to slow down? *Int. J. Sports Physiol. Perform.* 9, 442–445. doi: 10.1123/ijpspp.2013-0187
- Carling, C. (2013). Interpreting physical performance in professional soccer match-play: should we be more pragmatic in our approach? *Sports Med.* 43, 655–663. doi: 10.1007/s40279-013-0055-8
- Castellano, J., Casamichana, D., Calleja-González, J., Román, J., and Ostojic, S. (2011). Reliability and accuracy of 10 HZ GPS devices for short-distance exercise. *J. Sports Sci. Med.* 10, 233–234.



- Gaddam, V. R., Eg, R., Langseth, R., Griwodz, C., and Halvorsen, P. (2015). The cameraman operating my virtual camera is artificial: can the machine be as good as a human? *ACM Trans. Multimedia Comput. Commun. Appl.* 11, 56.1–56.20.
- Gaddam, V. R., Langseth, R., Stensland, H. K., Gurdjos, P., Charvillat, V., Griwodz, C., et al. (2014). “Be your own cameraman: real-time support for zooming and panning into stored and live panoramic video,” in *Proceedings of ACM MMSys* (Singapore), 168–171.
- Impellizzeri, F. M., Rampinini, E., Coutts, A. J., Sassi, A., and Marcora, S. M. (2004). Use of RPE-based training load in soccer. *Med. Sci. Sports Exerc.* 36, 1042–1047. doi: 10.1249/01.MSS.0000128199.23901.2F
- Jennings, D., Cormack, S., Coutts, A., Boyd, L., and RJ, A. (2010). Variability of GPS units for measuring distance in team sport movements. *Int. J. Sports Physiol. Perform.* 5, 565–574. doi: 10.1123/ijsp.5.4.565
- Johansen, D., Stenhaug, M., Hansen, R. B. A., Christensen, A., and Høgmo, P.-M. (2012). “Muithu: smaller footprint, potentially larger imprint,” in *Proceedings of IEEE ICDIM* (Algarve), 205–214.
- Johansen, H. D., Pettersen, S. A., Halvorsen, P., and Johansen, D. (2013). “Combining video and player telemetry for evidence-based decisions in soccer,” in *Proceedings of the International Congress on Sports Science Research and Technology Support (icSport)* (INSTICC) (Algarve), 197–205.
- Kunz, M. (2007). *Big Count: 265 Million Playing Football*. Fifa magazine, Federation Internationale de Football Association (FIFA).
- Langley, R. B. (1999). Dilution of precision. *GPS World* 10, 52–59.
- Mortensen, A., Gaddam, V. R., Stensland, H. K., Griwodz, C., Johansen, D., and Halvorsen, P. (2014). “Automatic event extraction and video summaries from soccer games,” in *Proceedings of ACM MMSys* (Singapore), 176–179.
- 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. *Med. Sci. Sports Exerc.* 42, 170–178. doi: 10.1249/MSS.0b013e3181ae5cfd
- Pettersen, S. A., Johansen, D., Johansen, H., Berg-Johansen, V., Gaddam, V. R., Mortensen, A., et al. (2014). “Soccer video and player position dataset,” in *Proceedings of ACM Multimedia Systems (MMSYS)* (Singapore).
- Saw, A. E., Main, L. C., and Gatin, P. B. (2015). Monitoring athletes through self-report: factors influencing implementation. *J. Sports Sci. Med.* 14, 137–149.
- Stensland, H. K., Gaddam, V. R., Tennøe, M., Helgedagsrud, E., Næss, M., Alstad, H. K., et al. (2014). Bagadus: An integrated real-time system for soccer analytics. *ACM Trans. Multimedia Comput. Commun. Appl.* 10:14. doi: 10.1145/2541011
- Stevens, T. G., de Ruiter, C. J., van Niel, C., van de Rhee, R., Beek, P. J., and Savelsbergh, G. J. (2014). Measuring acceleration and deceleration in soccer-specific movements using a local position measurement (LPM) system. *Int. J. Sports Physiol. Perform.* 9, 446–456. doi: 10.1123/ijsp.2013-0340
- Sweeting, A. J., Cormack, S. J., Morgan, S., and Aughey, R. J. (2017). When is a sprint a sprint? a review of the analysis of team-sport athlete activity profile. *Front. Physiol.* 8:432. doi: 10.3389/fphys.2017.00432

**Conflict of Interest Statement:** We hereby declare that PH is employed in a part-time position at ForzaSys AS.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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# **Paper 2**

RESEARCH ARTICLE

# Position specific player load during match-play in a professional football club

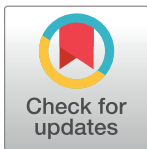
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## Abstract

There is a rapid growing body of knowledge regarding physical aspects of a football match due to studies using computer-assisted motion analysis. The present study used time-motion analysis and triaxial-accelerometers to obtain new insights about differences in physical profiles of elite football players across playing-positions. Player performance data in 23 official home matches from a professional football club, during two seasons were collected for analysis. Eighteen players from five different playing positions (central backs:  $n = 3$ ; full-backs:  $n = 5$ ; central midfielders:  $n = 6$ ; wide midfielders:  $n = 3$ ; and central forwards:  $n = 4$ ), performing a total of 138 observations. A novel finding was that central backs and central midfielders had significantly lower work-rate in sprints, decelerations and accelerations than full-backs, wide midfielders and central forwards ( $p < 0.001$ ). Furthermore, wide midfielders and full-backs performed significantly more turns ( $> 90^\circ$ ) than central backs. The most common distance covered in high-intensity runs ( $\geq 19.8 \text{ km} \cdot \text{h}^{-1}$ ) for central backs, central midfielders, wide midfielders and central forwards was 1–5 m, but for full-backs was 6–10 m. This may help coaches in developing individualized training programs to meet the demands of each position in match-play.



## OPEN ACCESS

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## Introduction

To understand physical demands of match-play in football objective data is essential and such data could be important for practitioners in designing training programs [1]. Of particular importance is the potential value objective data provide for personalized prescription of training load in a cohort of players following the same overall training regime.

Time motion analysis is commonly used in elite football to analyse player and team performance in training and match as it allows quantification of player running activities and indirect verification of the energetics of match-play [2], creating a rapid growing body of knowledge regarding the physical aspects of football training and match-play [3].

Football has a high-intensity intermittent nature [4], characterised by prolonged intermittent exercise interspersed by periods of maximal or close to maximal effort [5]. Players may be

required to repeat sprints, accelerations and turns of short duration interspersed by brief recovery periods over an extended period of time, and these activities have been reported as crucial factors for team performance [6–9].

Previous research has focused on the influence of different factors in the players' match running profiles, such as the tactical systems [10], possession status [11, 12], competitive standard [13], seasonal fluctuations [14], environment [15], opponent [16] and playing positions [17, 18].

Based on robust findings within the research literature, it is evident that specific playing positions have an influence on total match-load. Midfielders appear to cover the greatest overall distances (~11.5 km) while defenders and forwards cover lower distance (10–10.5 km) [4, 19–21]. Regarding high-intensity runs (HIR), the literature shows that, typically, wide midfielders (WM) and full-backs (FB) display superior HIR profiles [20, 22, 23] and central backs (CB) perform a significantly less amount of time sprinting and running with high intensity compared with other positions [1, 17].

The use of only distance and speed may underestimate the calculation of external player workload since this type of time-motion analysis has neglected some essential and specific movements of football (turns, accelerations, decelerations, etc.) that together appear numerous times during every match and may cause significant physical stress on the players [19, 24].

A previous study, with a Norwegian elite football team [24], combined data from triaxial accelerometer and time-motion analysis and experienced that player load was accumulated in a variety of ways across the different playing positions with accelerations and decelerations contributing 7–10% and 5–7%, respectively. Previous research has shown that players in lateral positions (FB and WM) accelerate more often, whereas CB and central midfielders (CM) decelerate less compared to other positions [24–26].

Therefore, the aims of the present study were to establish and compare the physical demands during official match-play in five different playing positions (CB, FB, CM, WM and central forwards [CF]) in a Norwegian elite football team using time-motion and triaxial-accelerometers.

## Methods

### Subjects and match analysis

With approval from UiT The Arctic University of Norway Institutional Review Board, written informed consent from players and approval from Norwegian Centre for Research Data, data on performance in 23 official home matches from the first team (highest level) in a Norwegian elite football club, during two seasons (2016 and 2017), were collected for analysis. The matches were all played on artificial grass surface (Alfheim Stadium, Tromsø, length = 110m; width = 68m). The sample included 18 players ( $25.2 \pm 4.4$  years;  $76.2 \pm 6.4$  kg;  $181.6 \pm 5.6$  cm; in age, body mass and height, respectively) across five different playing positions: CB ( $n = 3$ , observations[obs] = 35), FB ( $n = 5$ , obs = 34), CM ( $n = 6$ , obs = 38), WM ( $n = 3$ , obs = 18) and CF ( $n = 4$ , obs = 13), making a total of 138 observations. These positions were chosen according to team's main tactic formation and previous research [8, 18, 20, 24, 26, 27].

Data was analysed only if: (1) players completed the entire match, (2) the player played in the same position during all the match and (3) the team used 4-5-1 or 4-3-3 tactic formations.

To ensure players confidentiality, all data was anonymized before analyses.

### Procedures

A stationary radio-based tracking system (ZXY Sport Tracking System, Trondheim Norway) was used to characterize match activity profiles in the team. Each player wore a specially



designed belt, wrapped tightly around the waist, with an electronic sensor system at the player's lumbar spine [28]. The accuracy and reliability of the system in measuring player movements in elite soccer competitions have been described in more detail in previous studies [26, 28, 29].

### Physical performance variables

Physical parameters analysed included: number of accelerations ( $acc_{counts}$ ), acceleration distance per minute—work-rate—( $acc_{wr}$ ), number of decelerations ( $dec_{counts}$ ), deceleration work-rate ( $dec_{wr}$ ), HIR work-rate ( $HIR_{wr}$ ), HIR distance ( $HIR_{dist}$ ), sprint work-rate ( $sprint_{wr}$ ), sprint distance ( $sprint_{dist}$ ) and turns.

The following locomotor categories were selected: HIR ( $\geq 19.8 \text{ km}\cdot\text{h}^{-1}$ ) and sprinting ( $\geq 25.2 \text{ km}\cdot\text{h}^{-1}$ ). The speed thresholds applied for each locomotor categories are similar to those reported in previous research [16, 20, 24, 26].

According to the ZXY Sport Tracking system, accelerations are defined by four event markers: (1) the start of the acceleration event is marked by the acceleration reaching the minimum limit of  $1 \text{ m}\cdot\text{s}^{-2}$ , (2) the acceleration reaches the acceleration limit of  $2 \text{ m}\cdot\text{s}^{-2}$ , (3) the acceleration remains above the  $2 \text{ m}\cdot\text{s}^{-2}$  for at least 0.5 seconds and (4) the duration of the acceleration ends when it decreases below the minimum acceleration limit ( $1 \text{ m}\cdot\text{s}^{-2}$ ).

A turn was defined as a continuous and significant rotation of the body in one direction (derived from gyroscope and compass data). When a rotation in the opposite direction is measured, that will be the end of the previous turn and the start of the next turn. Due to the angle threshold used by ZXY Sport Tracking system only turns  $\geq 90$  degrees were analysed.

### Statistical analysis

Descriptive statistics (means and standard deviations) were calculated for the total sample and playing position.

Differences in match performance measures by field position were tested with a one-way analysis of variance (ANOVA). When significance was found, a Bonferroni post-hoc test was performed.

Effect sizes (ES), using Cohen's *d*, was calculated and interpreted as trivial ( $\leq 0.2$ ), small ( $>0.2-0.6$ ), moderate ( $>0.6-1.2$ ) and large ( $>1.2$ ). Significance level was set at 0.05 [30]. Statistical analyses were conducted using SPSS version 24.0.

## Results

### Acceleration and deceleration profiles

There were similar patterns in  $acc_{wr}$  and  $dec_{wr}$  with CB and CM performing less than FB, WM and CF, with the most significant difference being between CB ( $3.5 \pm 0.7$ ) and CF ( $5.3 \pm 1.0$ ) in  $dec_{wr}$  ( $p < 0.001$ ).

In relation to  $acc_{counts}$  and  $dec_{counts}$  WM presented higher values ( $76.7 \pm 12.1$ ;  $86.1 \pm 14.7$ ) than CB ( $64.9 \pm 9.7$ ;  $61.5 \pm 10.8$ ) and CM ( $65.8 \pm 15.6$ ;  $71.5 \pm 20.6$ ) ( $p < 0.001$ ), respectively.

Furthermore, all positions, except CB, performed less  $acc_{counts}$  than  $dec_{counts}$  during the entire match (Table 1).

### HIR and sprint profiles

Differences were observed in  $HIR_{WR}$  and  $Sprint_{wr}$  between CB and the other positions. CB had the lowest values of all positions in both variables but especially pronounced in  $Sprint_{wr}$  ( $0.9 \pm 0.5 \text{ m/min}$ ) when compared with CF ( $2.5 \pm 1.0 \text{ m/min}$ ) ( $p < 0.001$ ).

**Table 1. Descriptive statistic (mean and standard deviation) and ANOVA analysis (p-value) of different acceleration parameters analysed according to field position and respective Effect Size (ES) of differences observed.**

Variables	Central Backs	Full-backs	Central Midfielders	Wide Midfielders	Central Forwards	p-value	Post-hoc multiple comparisons (p<0.05)   Effect Size
Acc <sub>WR</sub> (m/min)	3.7 (0.7)	4.4 (0.6)	3.7 (1.2)	4.8 (0.9)	5.1 (1.3)	<0.001	CB<FB (0.25); CB<WM (0.33); CB<CF (0.39); FB>CM (0.26); CM<WM (0.34); CM<CF (0.40)
Acc <sub>COUNTS</sub> (total)	64.9 (9.7)	71.2 (11.6)	65.8 (15.6)	76.7 (12.1)	71.7 (12.0)	0.008	CB<WM (0.28); CM<WM (0.26)
Dec <sub>WR</sub> (m/min)	3.5 (0.7)	4.6 (0.7)	4.1 (1.4)	5.2 (0.9)	5.3 (1.0)	<0.001	CB<FB (0.39); CB<WM (0.50); CB<CF (0.48); CM<WM (0.31); CM<CF (0.31)
Dec <sub>COUNTS</sub> (total)	61.5 (10.8)	73.7 (14.0)	71.5 (20.6)	86.1 (14.7)	80.3 (14.6)	<0.001	CB<FB (0.29); CB<WM (0.47); CB<CF (0.33); CM<WM (0.28)

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Regarding HIR<sub>dist</sub>, CF presented higher values in 26–30 m than all the other positions, while distances of 36–40 and 46–50 m were covered more times by FB (1.7 ± 1.4; 0.9 ± 1.0). CB (0.8 ± 0.9; 0.2 ± 0.6) were the players with lowest values in these longer distances (36–40 and 46–50). Furthermore, distances of 1–5 m were the distances covered more often by CB, CM, WM and CF, whereas FB had higher values in distances of 6–10 m (Table 2).

In relation to sprint<sub>dist</sub> CB, FB, CM and WM performed higher number of 1–5 m, while CF covered higher number of 6–10 m sprints. (Table 3).

Furthermore, there was a pattern of covariance in the work-rates analysed (acc, dec, HIR and sprint) across playing positions (Fig 1).

**Table 2. Descriptive statistics statistic (mean and standard deviation) and ANOVA analysis (p-value) of different HIR distances and work-rate parameters analysed according to field position and respective Effect Size (ES) of differences observed.**

Variables	Central Backs	Full-backs	Central Midfielders	Wide Midfielders	Central Forwards	p-value	Post-hoc multiple comparisons (p<0.05)   Effect Size
HIR <sub>WR</sub> (m/min)	5.2 (1.6)	8.1 (1.7)	8.0 (3.5)	9.2 (1.8)	9.4 (1.6)	<0.001	CB<FB (0.46); CB<CM (0.46); CB<WM (0.54); CB<CF (0.51)
HIR <sub>DIST</sub> 1–5 m (counts)	8.2 (2.7)	7.5 (2.5)	9.2 (3.1)	10.3 (2.6)	9.3 (4.2)	0.009	FB<WM (0.27)
HIR <sub>DIST</sub> 6–10 m (counts)	7.6 (2.2)	8.3 (3.0)	8.2 (3.1)	8.9 (2.4)	8.2 (1.9)	0.591	No sig. differences
HIR <sub>DIST</sub> 11–15 m (counts)	5.0 (2.7)	6.6 (3.0)	6.3 (3.0)	8.1 (3.0)	6.4 (1.4)	0.008	CB<WM (0.33)
HIR <sub>DIST</sub> 16–20 m (counts)	4.8 (2.1)	5.0 (2.1)	5.2 (2.6)	5.8 (1.7)	6.0 (2.2)	0.301	No sig. differences
HIR <sub>DIST</sub> 21–25 m (counts)	2.6 (1.5)	3.7 (1.5)	3.7 (2.1)	4.2 (1.9)	5.2 (1.5)	<0.001	CB<WM (0.28); CB<CF (0.40)
HIR <sub>DIST</sub> 26–30 m (counts)	1.7 (1.1)	2.7 (1.4)	2.7 (1.8)	2.3 (1.0)	4.3 (1.2)	<0.001	CB<FB (0.26); CB<CF (0.50); FB<CF (0.31); CM<CF (0.33); WM<CF (0.35)
HIR <sub>DIST</sub> 31–35 m (counts)	1.1 (0.8)	1.7 (1.2)	2.2 (1.6)	3.4 (1.9)	2.8 (2.1)	<0.001	CB<CM (0.24); CB<WM (0.41); CB<CF (0.26); FB<WM (0.30)
HIR <sub>DIST</sub> 36–40 m (counts)	0.8 (0.9)	1.7 (1.4)	1.2 (1.1)	2.0 (0.8)	1.5 (1.1)	0.001	CB<FB (0.31); CB<WM (0.33)
HIR <sub>DIST</sub> 41–45 m (counts)	0.6 (0.9)	1.0 (1.1)	1.4 (1.3)	1.1 (1.0)	1.5 (1.0)	0.009	CB<CM (0.29)
HIR <sub>DIST</sub> 46–50 m (counts)	0.2 (0.6)	0.9 (1.0)	0.8 (0.9)	0.8 (1.1)	1.2 (1.4)	0.007	CB<FB (0.23); CB<CF (0.26)

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**Table 3. Descriptive statistics (mean and standard deviation) and ANOVA analysis (p-value) of different sprint distances and work-rate parameters analysed according field position and respective Effect Size (ES) of differences observed.**

Variables	Central Backs	Full-backs	Central Midfielders	Wide Midfielders	Central Forwards	p-value	Post-hoc multiple comparisons (p<0.05)   Effect Size
Sprint <sub>WR</sub> (m/min)	0.9 (0.5)	2.0 (0.6)	1.4 (1.0)	1.7 (0.7)	2.5 (1.0)	<0.001	CB<FB (0.49); CB<CM (0.26); CB<WM (0.32); CB<CF (0.55); FB>CM (0.24); CM<CF (0.37)
Sprint <sub>DIST</sub> 1–5 m (counts)	1.9 (1.2)	3.0 (1.7)	2.3 (1.9)	4.2 (1.7)	3.4 (1.6)	<0.001	CB<WM (0.42); CM<WM (0.35)
Sprint <sub>DIST</sub> 6–10 m (counts)	1.9 (1.5)	2.9 (1.2)	2.2 (1.8)	3.1 (1.6)	3.6 (2.5)	0.007	CB<CF (0.23)
Sprint <sub>DIST</sub> 11–15 m (counts)	1.0 (1.0)	2.2 (1.5)	1.5 (1.5)	1.8 (1.1)	2.3 (1.7)	0.008	CB<FB (0.29)
Sprint <sub>DIST</sub> 16–20 m (counts)	0.7 (0.7)	1.6 (1.2)	1.3 (1.5)	1.3 (0.9)	2.6 (1.6)	<0.001	CB<FB (0.25); CB<CF (0.40); CM<CF (0.28); WM<CF (0.26)
Sprint <sub>DIST</sub> 21–25 m (counts)	0.4 (0.6)	1.1 (0.9)	0.9 (1.1)	1.0 (0.9)	1.5 (1.1)	0.001	CB<FB (0.29); CB<CF (0.33)
Sprint <sub>DIST</sub> 26–30 m (counts)	0.3 (0.5)	0.7 (0.7)	0.5 (0.6)	0.5 (0.6)	0.4 (0.5)	0.087	No sig. differences
Sprint <sub>DIST</sub> 31–35 m (counts)	0.1 (0.3)	0.5 (0.6)	0.3 (0.6)	0.4 (0.7)	1.1 (0.8)	<0.001	CB<CF (0.42); FB<CF (0.26); CM<CF (0.34); WM<CF (0.25)
Sprint <sub>DIST</sub> 36–40 m (counts)	0.0 (1.7)	0.3 (0.5)	0.2 (0.4)	0.0 (0.0)	0.5 (0.7)	0.001	CB<FB (0.24); CB<CF (0.27); WM<CF (0.26)
Sprint <sub>DIST</sub> >41 m (counts)	0.3 (0.5)	0.4 (0.8)	0.2 (0.5)	0.4 (0.6)	0.2 (0.4)	0.436	No sig. differences

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### Turns

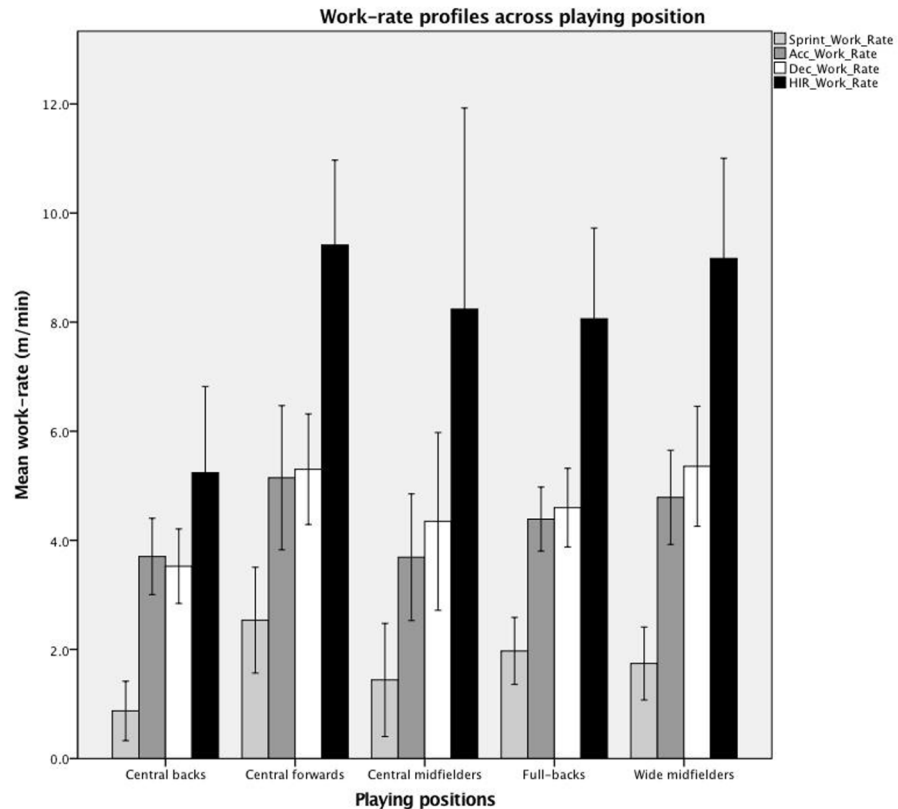
The main outcome was that CB performed less turns per match ( $32.7 \pm 10.1$ ) than FB ( $41.0 \pm 12.1$ ) and WM ( $42.9 \pm 12.3$ ) ( $p = 0.009$ ).

Moreover, turn angles,  $90^\circ$ - $180^\circ$  were the angles performed more often by all positions, while the turns with the highest angles ( $271^\circ$ - $360^\circ$ ) were the least common (Table 4).

### Discussion

The present study shows that the physical demands in official match-play, in elite football, vary greatly across playing positions. As previously mentioned, a novel finding from this study was that the work-rates in HIR, sprints, accelerations and decelerations change in the same pattern across playing positions. Although further research is needed to verify the correlation between these variables, our results demonstrate that CB and CM had significantly lower work-rate in sprints, accelerations and decelerations than FB, WM and CF with CB also having lower HIR<sub>wr</sub> than these three playing positions ( $p<0.001$ ). These findings are in line with the research literature regarding FB covering greater high-intensity and sprinting distances during matches compared to CB. [13, 18, 20, 31].

Previous studies have reported greater distances in HIR and sprint covered by wide players (FB and WM) compared with more central positions (CB, CM and CF) [13, 20, 24, 31], however the present study shows significant higher work-rate for wide positions only in acc, dec and sprints but not in HIR, even though the values for wide positions are slightly, though insignificantly, higher than for central positions (excluding CF). No significant differences were observed between CF and WM in HIR<sub>wr</sub> which is in line with previous research [18], but in opposition to others [11, 20, 31]. Furthermore, our data show that CF is the most physical demanding position with longer distances covered in HIR, sprints, accelerating and



**Fig 1. Work-rate profiles across playing position.** Mean work-rate in sprints, HIR, acc and dec.

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decelerating than the other positions. It has been speculated within the research literature that these differences between wide and more central positions are due to a lack of space for reaching sprinting velocity and the playing style (different roles for different positions) [24, 25, 32]. Taking into consideration the specific context of the club where our data was collected, it seems evident that the style of play (playing many times with low defence and in counter-attacking) had a crucial influence on position’s specific physical demands.

Table 2 illustrates that player position had a significant influence on the different distances covered in HIR. To the best of our knowledge, no previous research has characterized players’ HIR profiles regarding specific distances covered per HIR in official match-play across different playing positions. Our data show that while the most common distance covered in HIR for CB, CM, WM and CF was 1–5 m, for FB it was 6–10 m. An aspect to consider is that we also observed some HIR longer than the ones presented in Table 2 but with no significant differences between positions.

**Table 4. Descriptive statistics (mean and standard deviation) and ANOVA analysis (p-value) of different parameters of turns analysed according to field position and respective Effect Size (ES) of differences observed.**

Variables	Central Backs	Full-backs	Central Midfielders	Wide Midfielders	Central Forwards	p-value	Post-hoc multiple comparisons (p<0.05)   Effect Size
Turns	32.7 (10.1)	41.0 (12.1)	37.0 (12.4)	42.9 (12.3)	41.6 (12.9)	0.009	CB<FB (0.25); CB<WM (0.25)
Turns (90°-180°)	20.3 (6.3)	21.8 (7.2)	20.2 (7.4)	24.2 (6.9)	20.9 (5.7)	0.277	No sig. differences
Turns (181°-270°)	9.8 (5.3)	16.4 (6.1)	13.7 (5.0)	14.9 (6.4)	15.9 (7.8)	<0.001	CB<FB; CB<WM; CB<CF
Turns (271°-360°)	2.3 (1.9)	2.8 (2.1)	3.2 (2.1)	3.6 (1.9)	5.0 (1.9)	0.001	CB<CF; FB<CF

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Different patterns appear in  $\text{sprint}_{\text{dist}}$  with CB, FB, CM and WM covering more often shorter distances (1–5 m) in sprint while CF had higher values in longer distances (6–10 m).

Another important finding is that CF and WM accelerated more often compared with players in the other positions, which differs from a previous study with another Norwegian professional football club [24]. However, some similar trends were observed between these studies, with CB being the players who decelerated the least times compared with other playing positions. Furthermore, when comparing our data with results from previous research [4, 24, 25] we observed slightly lower values of  $\text{acc}_{\text{counts}}$  in almost all the positions (CB, FB, CM and WM). The inverse trend was observed in  $\text{dec}_{\text{counts}}$  with all positions presenting higher values in our study, probably due to style of play.

A main finding of the present study refers to the number of turns observed across playing positions. In fact, even though our study has taken into consideration only turns  $>90^\circ$  (angle threshold defined by ZXY Sport Tracking), total different values were obtained compared with previous research [17]. One difference is related to the total number of turns per match with our study presenting a mean of  $\sim 42 \pm 13$  to attackers (CF),  $\sim 39 \pm 13$  to midfielders (CM and WM) and  $\sim 37 \pm 12$  to defenders (CB and FB), while previous research [17] presented mean values significantly higher for each position: attackers ( $\sim 101$ ), midfielders ( $\sim 107$ ) and defenders ( $\sim 97$ ) in turns  $>90^\circ$ . They observed that midfielders performed significantly fewer turns during a match than defenders and strikers. Our data show that CM did not perform significantly different compared to the other positions while WM performed more turns than CB. These differences may be caused by the different sampling technology used.

Both turns, acceleration and deceleration activities add substantial load in addition to high-intensity running and must be taken into consideration when analysing physical demands of match-play.

It should be noted that different measurement technologies could cause the discrepancy in results between the present study and previous research [5]. Also, different playing styles, cultural and competitive contexts may account for differences observed.

In summary, our data show that speed and distance measures only to some extent predict the physical demands of a football player and that these demands vary greatly across playing positions. Taking into consideration the law of training specificity [33] and the idea that the physical loading of the training session should be individually designed to improve performance and avoid excess of fatigue and overtraining [34] the coaches need a clear view how different playing positions achieve load.

## Practical application

The present results may provide useful and novel insight regarding positional differences in physical profiles of elite football players during match-play. The positional differences in workload and work pattern need to be taken into consideration when designing and implementing training program cycles, according to the team's style of play. As for the team explored in the present study, lateral players should perform some longer sprints  $\geq 30$  m in normal training weeks to be prepared for these actions that appear during match. Performing sprints in addition to small sided games must be taken into consideration when planning the trainings since small and medium sided games do not provide enough space to elicit these actions.

Apart from providing valuable information to coaches about the activity profiles of different positions, the results may also provide the foundation for a real-time personalization computerized coach toolkit based on our whole-field video analysis system [35] that integrates with positional data in real-time. We are currently developing such a mobile system to customize individual training load to player positions while the practice is unfolding.

## Supporting information

**S1 File. Data review.**  
(SAV)

## Author Contributions

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## References

1. Ade J, Fitzpatrick J, Bradley PS. High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. *J Sports Sci.* 2016; 34(24):2205–14. Epub 2016/08/19. <https://doi.org/10.1080/02640414.2016.1217343> PMID: 27537056.
2. Carling C. Interpreting physical performance in professional soccer match-play: should we be more pragmatic in our approach? *Sports medicine (Auckland, NZ).* 2013; 43(8):655–63. Epub 2013/05/11. <https://doi.org/10.1007/s40279-013-0055-8> PMID: 23661303.
3. Paul DJ, Bradley PS, Nassis GP. Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *International journal of sports physiology and performance.* 2015; 10(4):516–9. Epub 2015/05/01. <https://doi.org/10.1123/IJSP.2015-0029> PMID: 25928752.
4. Bradley PS, Di Mascio M, Peart D, Olsen P, Sheldon B. High-intensity activity profiles of elite soccer players at different performance levels. *J Strength Cond Res.* 2010; 24(9):2343–51. Epub 2009/11/18. <https://doi.org/10.1519/JSC.0b013e3181aeb1b3> PMID: 19918194.
5. Randers MB, Mujika I, Hewitt A, Santisteban J, Bischoff R, Solano R, et al. Application of four different football match analysis systems: a comparative study. *J Sports Sci.* 2010; 28(2):171–82. Epub 2010/04/15. <https://doi.org/10.1080/02640410903428525> PMID: 20391091.
6. Bishop D, Spencer M, Duffield R, Lawrence S. The validity of a repeated sprint ability test. *J Sci Med Sport.* 2001; 4(1):19–29. Epub 2001/05/08. PMID: 11339490.
7. Carling C, Dupont G. Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *J Sports Sci.* 2011; 29(1):63–71. Epub 2010/11/16. <https://doi.org/10.1080/02640414.2010.521945> PMID: 21077004.
8. Carling C, Le Gall F, Dupont G. Analysis of repeated high-intensity running performance in professional soccer. *J Sports Sci.* 2012; 30(4):325–36. Epub 2012/01/18. <https://doi.org/10.1080/02640414.2011.652655> PMID: 22248291.
9. Girard O, Mendez-Villanueva A, Bishop D. Repeated-sprint ability—part I: factors contributing to fatigue. *Sports medicine (Auckland, NZ).* 2011; 41(8):673–94. Epub 2011/07/26. <https://doi.org/10.1185/11590550-000000000-00000> PMID: 21780851.
10. Bradley P, Carling C, Archer D, Roberts J, Dodds A, Di Mascio M, et al. The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *J Sports Sci.* 2011; 29(8):821–30. Epub 2011/04/23. <https://doi.org/10.1080/02640414.2011.561868> PMID: 21512949.
11. Bradley P, Lago-Penas C, Rey E, Gomez Diaz A. The effect of high and low percentage ball possession on physical and technical profiles in English FA Premier League soccer matches. *J Sports Sci.* 2013; 31(12):1261–70. Epub 2013/05/24. <https://doi.org/10.1080/02640414.2013.786185> PMID: 23697463.



12. Di Salvo V, Pigozzi F, Gonzalez-Haro C, Laughlin MS, De Witt JK. Match performance comparison in top English soccer leagues. *Int J Sports Med.* 2013; 34(6):526–32. Epub 2012/11/28. <https://doi.org/10.1055/s-0032-1327660> PMID: 23184481.
13. Bradley P, Carling C, Gomez Diaz A, Hood P, Barnes C, Ade J, et al. Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Human movement science.* 2013; 32(4):808–21. Epub 2013/08/28. <https://doi.org/10.1016/j.humov.2013.06.002> PMID: 23978417.
14. Mohr M, Krstrup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci.* 2003; 21(7):519–28. Epub 2003/07/10. <https://doi.org/10.1080/0264041031000071182> PMID: 12848386.
15. Mohr M, Nybo L, Grantham J, Racinais S. Physiological Responses and Physical Performance during Football in the Heat. *PLOS ONE.* 2012; 7(6):e39202. <https://doi.org/10.1371/journal.pone.0039202> PMID: 22723963
16. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri FM. Variation in top level soccer match performance. *Int J Sports Med.* 2007; 28(12):1018–24. Epub 2007/05/15. <https://doi.org/10.1055/s-2007-965158> PMID: 17497575.
17. Bloomfield J, Polman R, O'Donoghue P. Physical Demands of Different Positions in FA Premier League Soccer. *Journal of sports science & medicine.* 2007; 6(1):63–70. Epub 2007/01/01. PMID: 24149226; PubMed Central PMCID: PMCPMC3778701.
18. Schuth G, Carr G, Barnes C, Carling C, Bradley PS. Positional interchanges influence the physical and technical match performance variables of elite soccer players. *J Sports Sci.* 2016; 34(6):501–8. Epub 2015/12/25. <https://doi.org/10.1080/02640414.2015.1127402> PMID: 26700131.
19. Bangsbo J. The physiology of soccer—with special reference to intense intermittent exercise. *Acta physiologica Scandinavica Supplementum.* 1994; 619:1–155. Epub 1994/01/01. PMID: 8059610.
20. Bradley P, Sheldon W, Wooster B, Olsen P, Boanas P, Krstrup P. High-intensity running in English FA Premier League soccer matches. *J Sports Sci.* 2009; 27(2):159–68. Epub 2009/01/21. <https://doi.org/10.1080/02640410802512775> PMID: 19153866.
21. Rienzi E, Drust B, Reilly T, Carter JE, Martin A. Investigation of anthropometric and work-rate profiles of elite South American international soccer players. *The Journal of sports medicine and physical fitness.* 2000; 40(2):162–9. Epub 2000/10/18. PMID: 11034438.
22. Bush M, Barnes C, Archer DT, Hogg B, Bradley PS. Evolution of match performance parameters for various playing positions in the English Premier League. *Human movement science.* 2015; 39:1–11. Epub 2014/12/03. <https://doi.org/10.1016/j.humov.2014.10.003> PMID: 25461429.
23. Rampinini E, Impellizzeri FM, Castagna C, Abt G, Chamari K, Sassi A, et al. Factors influencing physiological responses to small-sided soccer games. *J Sports Sci.* 2007; 25(6):659–66. Epub 2007/04/25. <https://doi.org/10.1080/02640410600811858> PMID: 17454533.
24. Dalen T, Ingebrigtsen J, Ettema G, Hjelde GH, Wisloff U. Player Load, Acceleration, and Deceleration During Forty-Five Competitive Matches of Elite Soccer. *J Strength Cond Res.* 2016; 30(2):351–9. Epub 2015/06/10. <https://doi.org/10.1519/JSC.0000000000001063> PMID: 26057190.
25. Aughey RJ, Varley MC. Acceleration profiles in elite Australian soccer. *Int J Sports Med.* 2013; 34(3):282. Epub 2013/02/20. <https://doi.org/10.1055/s-0032-1331776> PMID: 23420194.
26. Ingebrigtsen J, Dalen T, Hjelde GH, Drust B, Wisloff U. Acceleration and sprint profiles of a professional elite football team in match play. *Eur J Sport Sci.* 2015; 15(2):101–10. Epub 2014/07/10. <https://doi.org/10.1080/17461391.2014.933879> PMID: 25005777.
27. Schimpchen J, Skorski S, Nopp S, Meyer T. Are "classical" tests of repeated-sprint ability in football externally valid? A new approach to determine in-game sprinting behaviour in elite football players. *J Sports Sci.* 2016; 34(6):519–26. Epub 2015/11/19. <https://doi.org/10.1080/02640414.2015.1112023> PMID: 26580089.
28. Bendiksen M, Pettersen SA, Ingebrigtsen J, Randers MB, Brito J, Mohr M, et al. Application of the Copenhagen Soccer Test in high-level women players—locomotor activities, physiological response and sprint performance. *Human movement science.* 2013; 32(6):1430–42. Epub 2013/09/11. <https://doi.org/10.1016/j.humov.2013.07.011> PMID: 24016711.
29. Andersen TB, Krstrup P, Bendiksen M, Orntoft CO, Randers MB, Pettersen SA. Kicking Velocity and Effect on Match Performance When using a Smaller, Lighter Ball in Women's Football. *Int J Sports Med.* 2016; 37(12):966–72. Epub 2016/11/05. <https://doi.org/10.1055/s-0042-109542> PMID: 27551936.
30. Cohen J. *Statistical Power Analysis for the Behavioral Sciences.* 2nd ed. Hillsdale NJ: Lawrence Erlbaum Associate; 1988.

31. Di Mascio M, Bradley PS. Evaluation of the most intense high-intensity running period in English FA premier league soccer matches. *J Strength Cond Res.* 2013; 27(4):909–15. Epub 2012/06/02. <https://doi.org/10.1519/JSC.0b013e31825ff099> PMID: 22652921.
32. Di Salvo V, Baron R, Gonzalez-Haro C, Gormasz C, Pigozzi F, Bachl N. Sprinting analysis of elite soccer players during European Champions League and UEFA Cup matches. *J Sports Sci.* 2010; 28(14):1489–94. Epub 2010/11/05. <https://doi.org/10.1080/02640414.2010.521166> PMID: 21049314.
33. Small K, McNaughton L, Greig M, Lovell R. Effect of timing of eccentric hamstring strengthening exercises during soccer training: implications for muscle fatigability. *J Strength Cond Res.* 2009; 23(4):1077–83. Epub 2009/06/17. <https://doi.org/10.1519/JSC.0b013e318194df5c> PMID: 19528859.
34. Rebelo AN, Silva P, Rago V, Barreira D, Krstrup P. Differences in strength and speed demands between 4v4 and 8v8 small-sided football games. *J Sports Sci.* 2016; 34(24):2246–54. Epub 2016/06/10. <https://doi.org/10.1080/02640414.2016.1194527> PMID: 27278256.
35. Stensland HK, Gaddam VR, Tennøe M, Helgedagsrud E, Næss M, Alstad HK, et al. Bagadus: An integrated real-time system for soccer analytics. *ACM Trans Multimedia Comput Commun Appl.* 2014; 10(1s):1–21. <https://doi.org/10.1145/2541011>



# **Paper 3**

## RESEARCH ARTICLE

# A comparison of match-physical demands between different tactical systems: 1-4-5-1 vs 1-3-5-2

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## Abstract

The team tactical system and distribution of the football players on the pitch is considered fundamental in team performance. The present study used time-motion analysis and triaxial-accelerometers to obtain new insights about the impact of different tactical systems (1-4-5-1 and 1-3-5-2) on physical performance, across different playing positions, in a professional football team. Player performance data in fifteen official home matches was collected for analysis. The sample included twenty-two players from five playing positions (centre backs:  $n = 4$ ; full-back/wide midfielder/ wing-back:  $n = 9$ ; centre midfielder:  $n = 6$  and centre forward:  $n = 3$ ), making a total of 108 match observations. A novel finding was that general match physical demands do not differ considerably between these tactical formations, probably because match-to-match variability (variation of players' running profile from match-to-match) might be higher than the differences in physical performance between tactical systems. However, change of formation had a different impact across playing positions, with centre backs playing in 1-4-5-1 performing significant more HIRcounts than in 1-3-5-2 ( $p = 0.031$ ). Furthermore, a medium effect size ( $r = 0.33$ ) was observed in HIRdist, with wide players covering higher distances when playing in 1-3-5-2 than in 1-4-5-1. These findings may help coaches to develop individualised training programs to meet the demands of each playing position according to the tactical system adopted.

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## Introduction

To better understand the constraints correlated with sporting success, match analysis has become an important tool in team sports. Nowadays it is well accepted among coaches and sport scientists that the match performance of a football team is, basically, based on four factors: physical, technical, tactical and mental [1]. Even though, the majority of research has been executed within the physical and technical performance domain, previous studies have

started to establish connections between physiological demands and tactical behaviour in elite football [2–5].

The lack of research and information about this field can be observed in a systematic review (2012–2016) on match analysis in adult male football [6], where the contextual variables of research analysed (match half, quality of opposition, match location, scoring first, group stage vs knockout phase, substitutions, competitive level and different competitions) did not include the tactical systems used by teams.

The team tactical system and the positioning and distribution of the players on the pitch is considered one of the most important strategic decisions in football [5, 7, 8] and, it is evident that player match-load is influenced by different factors, such as the playing position [2, 9, 10] and the tactical system [11]. This highlights the importance of understanding how physical demands may be affected by playing position in various tactical systems [6]. Despite some previous research [12, 13] addressing the team global positioning on the field, using the measures of centre and dispersion, the role of the tactical system regarding the players' physical performance, has not been fully described.

Previous studies have concluded that the manipulation of playing formations in small sided games promotes changes in physical performance of teams and players in training [14]. Also, the success of different tactics and strategies depend on the capacities and abilities of the players to perform specific actions during the match. Consequently, players must fulfil the necessary physiological requirements of their playing position inside the tactical system adopted [5, 15, 16].

Previous research has investigated the influence of opposition tactical formation on physiological performance variables and reported higher running distances when playing against a 1-4-2-3-1 formation compared to a 1-4-4-2 formation [17]. In opposition, other studies [11, 18] using various teams and/or different players across different seasons have concluded that tactical systems do not influence the match activity profiles of players. A pilot study with youth players [19] reported no correlation between physical/technical levels and tactical prominence in football matches. However, the identification of the tactical system adopted by a particular team is not a trivial step and previous studies have subjectively defined the tactical formations analysed by using qualified coaches to identify the different formations, as well as to verify if those formations were consistent throughout the game [17, 20]. To the best of our knowledge, no other study has examined the effect of playing formation on player load by position within the same team, in one full season.

An in-depth analysis of match physical performance across playing positions, in different tactical formations, could provide a better understanding of position-specific demands and provide an useful insight to optimize training programs [11]. Therefore, the present study aimed to analyse how tactical systems affect the physical performance of a professional football team across different playing positions in all official home matches during one season. We hypothesize that, despite playing in their specific position, players will accumulate different external workload in matches, depending on the tactical formation deployed.

## Methods

### Participants and match analysis

With institutional ethics approval from UiT The Arctic University of Norway Institutional Review Board, written informed consent from players and approval from the Norwegian Centre for Research Data, data on performance in 15 official home matches from the professional team of a Norwegian elite football club, during one season (2017), was collected for analysis. The matches were all played on artificial grass surface, as described in detail previously [10].

**Table 1. Number of match observations per player and tactical system.**

Player		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Observations per tactical system	1-4-5-1	3	5	7	1	3	5	1	0	6	2	4	2	6	0	6	0	1	1	1	0	1	1
	1-3-5-2	0	7	7	7	2	0	0	6	5	0	5	3	0	1	6	1	0	0	0	2	0	0
Total observations		3	12	14	8	5	5	1	6	11	2	9	5	6	1	12	1	1	1	1	2	1	1

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The sample included 22 players ( $25.2 \pm 4.4$  years of age;  $76.2 \pm 6.4$  kg of body mass; and,  $181.6 \pm 5.6$  cm of height) across four different playing positions: centre back, CB ( $n = 4$ , observations[obs] = 37), full-back/wide midfielder/ wing-back, FB/WM/WB ( $n = 9$ , obs = 31), centre midfielder, CM ( $n = 6$ , obs = 26), and centre forward, CF ( $n = 3$ , obs = 14), making a total of 139 match observations (Table 1). Playing-positions were chosen according to the two tactical formations used by the team and previous research [9, 21, 22]. Team tactical systems and playing positions were determined by two UEFA-qualified coaches (one from the coaching staff of the team analysed) after visualizing video recordings of the sampled matches [17, 20]. These observers subjectively determined the tactical systems used at the beginning of the match and verified if the formations were consistent throughout the matches [17]. Furthermore, 1-4-5-1 and 1-4-3-3 formations were combined, as well as 1-3-5-2 and 1-5-3-2. This procedure was applied due to difficulties in establishing specific differences between similar playing formations when in attacking and defending. When analysing the 1-3-5-2 formation the observers realized that the team often played in 1-5-3-2 formation when not in ball possession (defending) and in 1-3-5-2 with ball possession (attacking). On the other hand, when observing the 1-4-5-1 formation, the observers concluded that the team played in 1-4-5-1 when defending and in 1-4-3-3 when attacking [11, 17]. No other changes in formations throughout the matches were noticed by the observers, therefore no matches were excluded from the analysis.

Data was analysed only if: (a) players completed the full match (90 minutes), (b) the player played in the same position during all the match and (c) the team used 1-4-5-1 (1 goalkeeper; 2 CB + 2 FB; 3 CM + 2 WM; 1 CF) or 1-3-5-2 (1 goalkeeper; 3 CB; 3 CM + 2 WB; 2 CF) tactical formations during the entire match.

To ensure players confidentiality, all data was anonymized before analyses.

### Procedures

A stationary radio wave-based Local Positioning Measurement (LPM) tracking system (ZXY Sport Tracking System, Trondheim, Norway), with a default resolution of 20Hz, was used to characterize match activity profiles within the team. Each player wore a specially designed belt, wrapped tightly around the waist, with an electronic sensor system at the player’s lumbar spine, as reported previously [10]. At the stadium, where the matches occurred, there are 6 RadioEyes for optimal coverage, resulting in practically zero packet loss for transponders on the field. If packet loss occurred, the data was linearly interpolated. The accuracy and reliability of the system in measuring player movements in elite soccer competitions have been described in more detail in previous studies [23–25].

### Physical performance variables

Physical parameters analysed included: total distance (TotDist) number of accelerations ( $acc_{counts}$ ), acceleration distance ( $acc_{dist}$ ), number of decelerations ( $dec_{counts}$ ), deceleration

distance ( $\text{dec}_{\text{dist}}$ ), number of HIR ( $\text{HIR}_{\text{counts}}$ ), HIR distance ( $\text{HIR}_{\text{dist}}$ ), number of sprints ( $\text{sprint}_{\text{counts}}$ ), sprint distance ( $\text{sprint}_{\text{dist}}$ ) and turns.

The HIR ( $\geq 19.8 \text{ km}\cdot\text{h}^{-1}$ ) and sprinting ( $\geq 25.2 \text{ km}\cdot\text{h}^{-1}$ ) speed thresholds are similar to those reported in previous research [10, 22, 24, 26].

According to the ZXY Sport Tracking system accelerations were quantified through numerical derivation from positional data with a sampling frequency of 20Hz [25]. Furthermore, accelerations are defined by four event markers: (a) the start of the acceleration event is marked by the acceleration reaching the minimum limit of  $1 \text{ m}\cdot\text{s}^{-2}$ , (b) the acceleration reaches the acceleration limit of  $2 \text{ m}\cdot\text{s}^{-2}$ , (c) the acceleration remains above the  $2 \text{ m}\cdot\text{s}^{-2}$  for at least 0.5 seconds and (d) the duration of the acceleration ends when it decreases below the minimum acceleration limit ( $1 \text{ m}\cdot\text{s}^{-2}$ ).

Turns were counted only if the player performed a continuous and significant body rotation of more than  $90^\circ$  in one direction (derived from gyroscope and compass data). The end of a turn and the start of another occurs when a rotation in the opposite direction is measured. The angle threshold used by ZXY Sport Tracking system allowed us to analyse only angles  $\geq 90^\circ$ .

## Statistical analysis

The results are presented as mean and 95% confidence interval, unless otherwise stated. A linear mixed-effects model with restricted maximum likelihood estimations was used to examine differences in Local Positioning Measurement-derived variables and match duration between 1-3-5-2 and 1-4-5-1 formations. Mixed models can account for unbalanced repeats per player and thus used to model the data. Tactical formation, playing position and their interaction was modelled as fixed effects (effects describing the association between the dependent variable and covariates), while 'athlete ID' was included as a random effect (effects generally representing random deviations from the relationships of the fixed part of the model). An  $\alpha$ -level of 0.05 was used as level of significance for statistical comparisons. Furthermore, multiple comparisons were adjusted using the Tukey method. The t statistics from the mixed models were converted to effect size correlations [27]. Effect sizes were interpreted as  $<0.1$ , trivial; 0.1–0.3, small; 0.3–0.5, moderate; 0.5–0.7, large; 0.7–0.9, very large; 0.9–0.99, almost perfect; 1.0, perfect [28]. All statistical analyses were conducted using the lme4, lsmeans and psychometric packages in R statistical software (version 3.4.1, R Foundation for Statistical Computing, Vienna, Austria).

## Results

### Centre-backs

Slightly higher values, though not statistically significant, were found in  $\text{HIR}_{\text{dist}}$ , Acc and Dec (counts and distance),  $\text{sprint}_{\text{counts}}$  and turns when playing in 1-4-5-1 compared to 1-3-5-2 formation (Table 2). Furthermore, CB playing in 1-4-5-1 were observed to perform significant more  $\text{HIR}_{\text{counts}}$  ( $36.1 \pm 3.5$ ) than in 1-3-5-2 ( $28.2 \pm 3.5$ ) ( $p = 0.008$ ), with a correspondent medium effect size ( $r = 0.37$ ).

### Wide positions

No significant differences were observed between the tactical formations analysed from players playing in wide positions (Table 3). However, higher values in  $\text{HIR}_{\text{dist}}$  ( $r = 0.19$ ) and  $\text{sprint}_{\text{dist}}$  ( $r = 0.16$ ) were found when playing with 1-3-5-2 ( $977.2 \pm 73.7$ ;  $236.9 \pm 26.8$ ) compared to 1-4-5-1 ( $838.9 \pm 62.5$ ;  $195.3 \pm 22.7$ ) formation.

**Table 2. Mean and 95% confidence interval estimates of different physical parameters from centre backs, analysed according to the tactical system used, and respective p-value and effect size of differences observed (n = 4; observations = 37).**

Variables	CB		p-value	Effect Size (r)
	1-4-5-1	1-3-5-2		
TotDist (m)	10865.0 (227.6)	10591.8 (224.0)	0.825	0.15
HIR <sub>counts</sub>	36.1 (3.5)	28.2 (3.5)	0.008	0.37
HIR <sub>dist</sub> (m)	512.0 (81.5)	431.0 (81.3)	0.658	0.18
Sprint <sub>counts</sub>	6.6 (1.9)	5.4 (1.9)	0.871	0.15
Sprint <sub>dist</sub> (m)	64.4 (29.6)	74.2 (29.5)	0.999	0.06
Acc <sub>dist</sub> (m)	325.6 (37.6)	306.9 (37.6)	0.982	0.10
Acc <sub>counts</sub>	63.2 (6.1)	59.7 (6.1)	0.983	0.10
Dec <sub>dist</sub> (m)	321.2 (41.7)	278.5 (41.6)	0.543	0.20
Dec <sub>counts</sub>	60.3 (6.9)	53.6 (6.9)	0.680	0.18
Turns	32.2 (3.5)	25.8 (3.4)	0.437	0.21

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### Centre midfielders

Small effect sizes were observed in HIR<sub>counts</sub> (r = 0.12) and Acc<sub>counts</sub> (r = 0.14) (Table 4), with higher values being observed when playing in 1-4-5-1 (38.5 ± 3.2; 62.3 ± 5.5) than in 1-3-5-2 (35.7 ± 3.4; 55.9 ± 5.9). A similar effect size was also observed in turns (r = 0.15), with CM performing more turns when playing in 1-3-5-2 (40.3 ± 3.7) than in 1-4-5-1 (34.7 ± 3.4).

### Centre forwards

No significant differences were found regarding any parameter analysed. However, higher values, though with a trivial effect size, in HIR<sub>dist</sub> and sprint<sub>dist</sub> can be observed (Table 5) when playing in 1-3-5-2.

### Tactical system

Significant differences were found in various parameters when comparing the physical performance of the whole team when playing with different tactical systems (Table 6). Significant higher values were observed in HIR<sub>counts</sub> (r = 0.25) and sprint<sub>counts</sub> (r = 0.22) when playing in

**Table 3. Mean and 95% confidence interval estimates of different physical parameters from full-backs, wide midfielders and wing-backs analysed according to the tactical system used, and respective p-value and effect size of differences observed (n = 9; observations = 31).**

Variables	FB/WM/WB		p-value	Effect Size (r)
	1-4-5-1	1-3-5-2		
TotDist	10842.6 (188.8)	11143.0 (233.0)	0.942	0.13
HIR <sub>counts</sub>	45.9 (2.7)	46.9 (3.2)	1.000	0.03
HIR <sub>dist</sub>	838.9 (62.5)	977.2 (73.7)	0.523	0.19
Sprint <sub>counts</sub>	14.1 (1.4)	14.0 (1.6)	1.000	0.01
Sprint <sub>dist</sub>	195.3 (22.7)	236.9 (26.8)	0.747	0.16
Acc <sub>dist</sub>	462.2 (28.5)	447.1 (33.2)	1.000	0.05
Acc <sub>counts</sub>	83.2 (4.7)	76.8 (5.7)	0.950	0.12
Dec <sub>dist</sub>	501.2 (31.5)	505.4 (36.9)	1.000	0.01
Dec <sub>counts</sub>	86.9 (5.3)	86.1 (6.2)	1.000	0.01
Turns	42.1 (2.9)	38.8 (3.7)	0.993	0.11

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**Table 4.** Mean and 95% confidence interval estimates of different physical parameters from centre midfielders, analysed according to the tactical system used, and respective p-value and effect size of differences observed (n = 6; observations = 26).

Variables	CM		p-value	Effect Size (r)
	1-4-5-1	1-3-5-2		
TotDist	12009.0 (218.5)	11820.8 (238.7)	1.000	0.09
HIR <sub>counts</sub>	38.5 (3.2)	35.7 (3.4)	0.948	0.12
HIR <sub>dist</sub>	643.2 (73.1)	610.9 (78.1)	1.000	0.06
Sprint <sub>counts</sub>	7.0 (1.6)	7.0 (1.7)	1.000	0.05
Sprint <sub>dist</sub>	101.4 (26.6)	94.8 (28.4)	1.000	0.03
Acc <sub>dist</sub>	313.3 (33.4)	289.6 (35.5)	0.973	0.10
Acc <sub>counts</sub>	62.3 (5.5)	55.9 (5.9)	0.845	0.14
Dec <sub>dist</sub>	358.3 (37.0)	326.0 (39.4)	0.923	0.13
Dec <sub>counts</sub>	69.4 (6.2)	64.2 (6.6)	0.951	0.11
Turns	34.7 (3.4)	40.3 (3.7)	0.782	0.15

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1-4-5-1 ( $43.6 \pm 1.9$ ;  $11.4 \pm 1.1$ ) compared with 1-3-5-2 ( $40.0 \pm 2.0$ ;  $10.0 \pm 1.1$ ) ( $p = 0.005$  and  $p = 0.015$ , respectively). Furthermore, when playing in 1-4-5-1, the team was observed to perform more Acc<sub>counts</sub> ( $75.8 \pm 3.2$ ) and Dec<sub>counts</sub> ( $77.8 \pm 3.5$ ), as well as covering higher distances in Dec<sub>dist</sub> ( $440.3 \pm 23.3$ ) than when playing in 1-3-5-2 ( $71.1 \pm 3.4$ ;  $72.5 \pm 3.6$ ;  $413.7 \pm 24.2$ ; for Acc<sub>counts</sub>, Dec<sub>counts</sub> and Dec<sub>dist</sub>) ( $p = 0.022$ ;  $p = 0.014$  and  $p = 0.032$ , respectively).

## Discussion

### Context

The present study provides new insights into the physical demands of two common tactical formations, in elite football players across different playing positions. The context of this study appeared with the change of the head-coach, and consequently, the tactical formation and style of play used of the professional football team analysed. Since this replacement happened in the middle of the season, both tactical formations analysed were composed by an almost equal number of matches (7 and 8 home matches each). It is also important to refer that the change of head-coach led not only to a simple switch of the tactical structure used, but also to a change to a more complex style of play. A more possession and position-oriented style of play

**Table 5.** Mean and 95% confidence interval estimates of different physical parameters from centre forwards, analysed according to the tactical system used, and respective p-value and effect size of differences observed (n = 3; observations = 14).

Variables	CF		p-value	Effect Size (r)
	1-4-5-1	1-3-5-2		
TotDist	10724.4 (328.6)	10732.8 (328.6)	1.000	>0.01
HIR <sub>counts</sub>	48.6 (4.7)	47.1 (4.7)	1.000	0.05
HIR <sub>dist</sub>	835.2 (108.5)	930.5 (108.5)	0.881	0.14
Sprint <sub>counts</sub>	11.7 (2.4)	12.8 (2.4)	0.993	0.08
Sprint <sub>dist</sub>	164.5 (39.5)	208.5 (39.5)	0.689	0.18
Acc <sub>dist</sub>	483.4 (49.4)	477.7 (49.4)	1.000	0.02
Acc <sub>counts</sub>	82.9 (8.2)	80.2 (8.2)	1.000	0.05
Dec <sub>dist</sub>	461.4 (54.8)	470.8 (54.8)	1.000	0.03
Dec <sub>counts</sub>	78.3 (9.2)	73.4 (9.2)	0.992	0.09
Turns	36.8 (5.1)	29.7 (5.1)	0.810	0.16

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**Table 6. Mean and 95% confidence interval estimates of different physical parameters from the whole team, analysed according to the tactical system used, and respective p-value and effect size of differences observed.**

Variables	Tactical system		p-value	Effect Size (r)
	1-4-5-1	1-3-5-2		
TotDist	11048.5 (140.2)	11091.2 (149.5)	0.705	0.03
HIR <sub>counts</sub>	43.6 (1.9)	40.0 (2.0)	0.005	0.25
HIR <sub>dist</sub>	779.9 (50.9)	762.8 (52.7)	0.541	0.06
Sprint <sub>counts</sub>	11.4 (1.1)	10.0 (1.1)	0.015	0.22
Sprint <sub>dist</sub>	156.9 (19.1)	158.6 (19.8)	0.867	0.02
Acc <sub>dist</sub>	420.7 (23.1)	401.1 (23.8)	0.085	0.16
Acc <sub>counts</sub>	75.8 (3.2)	71.1 (3.4)	0.022	0.20
Dec <sub>dist</sub>	440.3 (23.3)	413.7 (24.2)	0.032	0.19
Dec <sub>counts</sub>	77.8 (3.5)	72.5 (3.6)	0.014	0.22
Turns	36.9 (1.9)	33.5 (2.0)	0.057	0.16

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were adopted (1-3-5-2) instead of the more direct play and counter-attack strategy used in the first half of the season (1-4-5-1). However, even with all these changes, the context remained the same (same players with similar physical capacities).

### Comparison according to playing position

The results suggest that general match physical demands do not differ considerably between these two tactical formations when compared by playing position. Independent of formation and with few exceptions, players presented similar profiles in all the physical parameters analysed. The most relevant exceptions were the higher HIR<sub>counts</sub> in CB (1-4-5-1) and longer HIR<sub>dist</sub> in FB/WM/WB (1-3-5-2), with a medium and small effect size, respectively.

CB playing in 1-4-5-1 performed more HIR<sub>counts</sub>, probably due to the larger area they needed to cover when compared to the area covered by the three CBs when playing in 1-3-5-2. When in defensive organisation (without ball possession), the defensive line of three CBs became most of the time a defensive line composed by 5 players (three CBs and two WBs). The increased number of players playing in the defensive line leads to less m<sup>2</sup> per player to cover.

Players in wide positions covered more HIR<sub>dist</sub> when playing in 1-3-5-2 most likely because in this formation the team played with only two wide players (WB), and they needed to cover all the flank, while with 1-4-5-1 formation, those flanks were covered by a total of four players (two on each side).

It has been speculated that match physical demands are higher for CF when playing “alone” in the offensive line (e.g. 1-4-5-1; 1-5-4-1), as they are very often isolated and marked by several opponents [29]. However, the results of the present study are slightly different, since higher, though not significant, values were found in HIR<sub>dist</sub> and sprint<sub>dist</sub> for CF, when playing with two attackers (1-3-5-2) compared with playing with only one (1-4-5-1).

Furthermore, no differences in playing time (substitutions) were observed in any playing position between the two tactical systems analysed.

### Comparison according to team workload

When playing position was not taken into consideration and the work-load of the whole team was analysed, the physical workload in some variables was significantly different between tactical systems used. Small significant differences were observed in HIR<sub>counts</sub> and sprint<sub>counts</sub>, with the team performing more runs (>19,8 km/h) when playing in 1-4-5-1. The number of Acc



and Dec was also higher when the 1-4-5-1 system was used. In general, almost all variables analysed presented higher values during the first period of the season (1-4-5-1) than in the second (1-3-5-2).

Previous research [30, 31] has suggested that teams who are winning the match tend to relax and decrease their work-rate. Alternatively, although teams who are losing the match may increase their work-rate during a specified period [32, 33], they may quickly lose the motivation to keep the elevated work rate, which may be especially evident when the goal difference increases negatively (conceding more goals) [34]. In fact, the differences observed between these two tactical systems might be, in part, justified by the significant discrepancy between the score line and match final results achieved during the first and second part of the season. While playing in 1-4-5-1 the team achieved one victory, four draws and three defeats in the eight home matches played. On the other hand, while playing in 1-3-5-2, the team had better results, with five victories, one draw and one defeat in the last seven home matches played. The match results (considerably more draws) and the differences in style of play may therefore, partly justify the higher work-rate of the 1-4-5-1 tactical system.

### Limitations

Our initial hypothesis was that, despite playing in their specific positions, players would accumulate different external workload in matches, depending on the preferred tactical formation. However, the results presented in this study do not fully support the hypothesis, probably because the match-to-match variability might be larger than the differences in physical performance between tactical systems. Like most of the measures in team sports performance, the physical variables used in this study are not stable and are subject to a high variation between successive matches [35]. Furthermore, it has been proved that within-subject (player) and between-match variation in physical performance across the season might be experienced due to changes in the physical condition of the player [36, 37] and environmental conditions [38]. Previous studies have shown that match-to-match variability in performance characteristics of elite soccer players is high [35, 39, 40] and that future research based in match performance requires large sample sizes to identify true systematic changes in workload. In fact, the sample size (22 players/108 observations) might be of such small numbers that true differences can be masked due to a statistical type 2 error, and such a consequence cannot be conclusively ruled out. Previous similar studies have analysed more matches [17] or used considerably larger sample sizes [11] than in the present study. However, they have not compared the physical demands of different tactical systems within the same players in the same context (same team and season) and to do so, a larger sample size than the one used in the present study becomes a difficult task to fulfil.

Even though, the methodology used to determine the team formations is in line with previous studies [11, 14, 17, 20, 41, 42], the process of defining team formations and controlling their consistency throughout the matches was based on the subjective assessment of observers. Further research is needed to attempt to define objectively team formations and to identify when changes occur [17].

Goalkeepers were not included in the present study, however their match activity profiles might be useful and interesting to analyse in different tactical systems and styles of play in future research. All these limitations should be taken into consideration when designing future studies.

### Perspectives and practical application

Since previous research has shown that the players' physical demands in matches are highly dependent on their positional role in the team [43, 44], analytics, in general, have become a

crucial component of team organization and content of training, to meet the position-specific requirements of physical conditioning [45]. This study goes beyond the individualization of training demands according to playing position, also suggesting that the change of tactical system might influence, specific variables of the team's overall match activity profile, and those differences should be taken into consideration when designing training programs. On the other hand, differences are not notable in all playing positions and these findings should be interpreted with caution, as differences might be team dependent since other teams using the same tactical systems, probably appear with different styles of play.

Change of formation had a different impact on different playing positions, with CB and wide positions presenting more substantial differences than CM and CF. As previously mentioned, the present study and its findings may provide useful and novel insights for coaches on physical performance demands in different tactical formations across playing positions. The information provided should be taken into consideration when designing and implementing training program cycles, according to players' playing position, the team's tactical formation and style of play. The individualization and specialization of the training should, therefore, be a matter of reflection and analysis from practitioners.

## Supporting information

**S1 File. Data review.**  
(XLSX)

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## References

1. Sarmento H, Marcelino R, Anguera MT, CampaniCo J, Matos N, LeitAo JC. Match analysis in football: a systematic review. *J Sports Sci.* 2014; 32(20):1831–43. Epub 2014/05/03. <https://doi.org/10.1080/02640414.2014.898852> PMID: 24787442.
2. Bloomfield J, Polman R, O'Donoghue P. Physical Demands of Different Positions in FA Premier League Soccer. *Journal of sports science & medicine.* 2007; 6(1):63–70. Epub 2007/01/01. PMID: 24149226; PubMed Central PMCID: PMCPMC3778701.
3. Drust B, Atkinson G, Reilly T. Future perspectives in the evaluation of the physiological demands of soccer. *Sports medicine (Auckland, NZ).* 2007; 37(9):783–805. Epub 2007/08/29. <https://doi.org/10.2165/00007256-200737090-00003> PMID: 17722949.

4. Moura FA, Martins LE, Anido Rde O, de Barros RM, Cunha SA. Quantitative analysis of Brazilian football players' organisation on the pitch. *Sports biomechanics*. 2012; 11(1):85–96. Epub 2012/04/24. <https://doi.org/10.1080/14763141.2011.637123> PMID: 22518947.
5. Rein R, Memmert D. Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. SpringerPlus. 2016; 5(1):1410. Epub 2016/09/10. <https://doi.org/10.1186/s40064-016-3108-2> PMID: 27610328; PubMed Central PMCID: PMC4996805.
6. Sarmento H, Clemente FM, Araujo D, Davids K, McRobert A, Figueiredo A. What Performance Analysts Need to Know About Research Trends in Association Football (2012–2016): A Systematic Review. *Sports medicine (Auckland, NZ)*. 2018; 48(4):799–836. Epub 2017/12/16. <https://doi.org/10.1007/s40279-017-0836-6> PMID: 29243038.
7. Kannekens R, Elferink-Gemser MT, Visscher C. Positioning and deciding: key factors for talent development in soccer. *Scandinavian Journal of Medicine & Science in Sports*. 2011; 21(6):846–52. <https://doi.org/10.1111/j.1600-0838.2010.01104.x> PMID: 22126715
8. Sampaio J, Macas V. Measuring tactical behaviour in football. *Int J Sports Med*. 2012; 33(5):395–401. Epub 2012/03/02. <https://doi.org/10.1055/s-0031-1301320> PMID: 22377947.
9. Schuth G, Carr G, Barnes C, Carling C, Bradley PS. Positional interchanges influence the physical and technical match performance variables of elite soccer players. *J Sports Sci*. 2016; 34(6):501–8. Epub 2015/12/25. <https://doi.org/10.1080/02640414.2015.1127402> PMID: 26700131.
10. Baptista I, Johansen D, Seabra A, Pettersen SA. Position specific player load during match-play in a professional football club. *PLoS One*. 2018; 13(5). <https://doi.org/10.1371/journal.pone.0198115> PMID: 29795703; PubMed Central PMCID: PMC5967838.
11. Bradley P, Carling C, Archer D, Roberts J, Dodds A, Di Mascio M, et al. The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *J Sports Sci*. 2011; 29(8):821–30. Epub 2011/04/23. <https://doi.org/10.1080/02640414.2011.561868> PMID: 21512949.
12. Bartlett R, Button C, Robins M, Dutt-Mazumder A, Kennedy G. Analysing Team Coordination Patterns from Player Movement Trajectories in Soccer: Methodological Considerations. *International Journal of Performance Analysis in Sport International Journal of Performance Analysis in Sport*. 2017; 12(2):398–424.
13. Moura FA, Martins LE, Anido RO, Ruffino PR, Barros RM, Cunha SA. A spectral analysis of team dynamics and tactics in Brazilian football. *J Sports Sci*. 2013; 31(14):1568–77. Epub 2013/05/02. <https://doi.org/10.1080/02640414.2013.789920> PMID: 23631771.
14. Baptista J, Travassos B, Goncalves B, Mourao P, Viana JL, Sampaio J. Exploring the effects of playing formations on tactical behaviour and external workload during football small-sided games. *J Strength Cond Res*. 2018. Epub 2018/01/18. <https://doi.org/10.1519/jsc.0000000000002445> PMID: 29337830.
15. Clemente FM, Couceiro MS, Martins FM, Ivanova MO, Mendes R. Activity profiles of soccer players during the 2010 world cup. *J Hum Kinet*. 2013; 38:201–11. Epub 2013/11/16. <https://doi.org/10.2478/hukin-2013-0060> PMID: 24235995; PubMed Central PMCID: PMC3827759.
16. Silva JR, Magalhaes J, Ascensao A, Seabra AF, Rebelo AN. Training status and match activity of professional soccer players throughout a season. *J Strength Cond Res*. 2013; 27(1):20–30. Epub 2012/02/22. <https://doi.org/10.1519/JSC.0b013e31824e1946> PMID: 22344051.
17. Carling C. Influence of opposition team formation on physical and skill-related performance in a professional soccer team. *European Journal of Sport Science*. 2011; 11(3):155–64. <https://doi.org/10.1080/17461391.2010.499972>
18. Palucci Vieira LH, Aquino R, Lago-Penas C, Munhoz Martins GH, Puggina EF, Barbieri FA. Running Performance in Brazilian Professional Football Players During a Congested Match Schedule. *J Strength Cond Res*. 2018; 32(2):313–25. Epub 2018/01/26. <https://doi.org/10.1519/JSC.0000000000002342> PMID: 29369952.
19. Clemente FM, Figueiredo AJ, Martins FM, Mendes RS, Wong DP. Physical and technical performances are not associated with tactical prominence in U14 soccer matches. *Research in sports medicine (Print)*. 2016; 24(4):352–62. Epub 2016/10/30. <https://doi.org/10.1080/15438627.2016.1222277> PMID: 27533018.
20. Aquino R, Carling C, Palucci Vieira LH, Martins G, Jabor G, Machado J, et al. Influence of Situational Variables, Team Formation, and Playing Position on Match Running Performance and Social Network Analysis in Brazilian Professional Soccer Players. *J Strength Cond Res*. 2018. Epub 2018/07/10. <https://doi.org/10.1519/jsc.0000000000002725> PMID: 29985222.
21. Carling C, Le Gall F, Dupont G. Analysis of repeated high-intensity running performance in professional soccer. *J Sports Sci*. 2012; 30(4):325–36. Epub 2012/01/18. <https://doi.org/10.1080/02640414.2011.652655> PMID: 22248291.

22. Bradley P, Sheldon W, Wooster B, Olsen P, Boanas P, Krstrup P. High-intensity running in English FA Premier League soccer matches. *J Sports Sci.* 2009; 27(2):159–68. Epub 2009/01/21. <https://doi.org/10.1080/02640410802512775> PMID: 19153866.
23. Bendiksen M, Pettersen SA, Ingebrigtsen J, Randers MB, Brito J, Mohr M, et al. Application of the Copenhagen Soccer Test in high-level women players—locomotor activities, physiological response and sprint performance. *Human movement science.* 2013; 32(6):1430–42. Epub 2013/09/11. <https://doi.org/10.1016/j.humov.2013.07.011> PMID: 24016711.
24. Ingebrigtsen J, Dalen T, Hjelde GH, Drust B, Wisloff U. Acceleration and sprint profiles of a professional elite football team in match play. *Eur J Sport Sci.* 2015; 15(2):101–10. Epub 2014/07/10. <https://doi.org/10.1080/17461391.2014.933879> PMID: 25005777.
25. Pettersen SA, Johansen HD, Baptista IAM, Halvorsen P, Johansen D. Quantified Soccer Using Positional Data: A Case Study. *Frontiers in Physiology.* 2018; 9(866). <https://doi.org/10.3389/fphys.2018.00866> PMID: 30034347
26. Dalen T, Ingebrigtsen J, Ettema G, Hjelde GH, Wisloff U. Player Load, Acceleration, and Deceleration During Forty-Five Competitive Matches of Elite Soccer. *J Strength Cond Res.* 2016; 30(2):351–9. Epub 2015/06/10. <https://doi.org/10.1519/JSC.0000000000001063> PMID: 26057190.
27. Rosnow RL, Rosenthal R, Rubin DB. Contrasts and correlations in effect-size estimation. *Psychological science.* 2000; 11(6):446–53. Epub 2001/02/24. <https://doi.org/10.1111/1467-9280.00287> PMID: 11202488.
28. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Medicine and science in sports and exercise.* 2009; 41(1):3–13. Epub 2008/12/19. <https://doi.org/10.1249/MSS.0b013e31818cb278> PMID: 19092709.
29. Bangsbo J, Peitersen B. Soccer systems and strategies. Champaign IL: Human Kinetics; 2000.
30. Lago C. The influence of match location, quality of opposition, and match status on possession strategies in professional association football. *J Sports Sci.* 2009; 27(13):1463–9. Epub 2009/09/17. <https://doi.org/10.1080/02640410903131681> PMID: 19757296.
31. Paul DJ, Bradley PS, Nassiss GP. Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *Int J Sports Physiol Perform.* 2015; 10(4):516–9. <https://doi.org/10.1123/IJSP.2015-0029> PMID: 25928752.
32. Castellano J, Blanco-Villasenor A, Alvarez D. Contextual variables and time-motion analysis in soccer. *Int J Sports Med.* 2011; 32(6):415–21. Epub 2011/05/19. <https://doi.org/10.1055/s-0031-1271771> PMID: 21590641.
33. Lago-Penas C, Dellal A. Ball possession strategies in elite soccer according to the evolution of the match-score: the influence of situational variables. *J Hum Kinet.* 2010; 25:93–100.
34. Redwood-Brown AJ, O'Donoghue PG, Nevill AM, Saward C, Dyer N, Sunderland C. Effects of situational variables on the physical activity profiles of elite soccer players in different score line states. *Scand J Med Sci Sports.* 2018. Epub 2018/07/29. <https://doi.org/10.1111/sms.13271> PMID: 30055045.
35. Gregson W, Drust B, Atkinson G, Salvo VD. Match-to-match variability of high-speed activities in premier league soccer. *Int J Sports Med.* 2010; 31(4):237–42. Epub 2010/02/17. <https://doi.org/10.1055/s-0030-1247546> PMID: 20157871.
36. Krstrup P, Bangsbo J. Physiological demands of top-class soccer refereeing in relation to physical capacity: effect of intense intermittent exercise training. *J Sports Sci.* 2001; 19(11):881–91. Epub 2001/11/07. <https://doi.org/10.1080/026404101753113831> PMID: 11695510.
37. Mohr M, Krstrup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci.* 2003; 21(7):519–28. Epub 2003/07/10. <https://doi.org/10.1080/0264041031000071182> PMID: 12848386.
38. Ekblom B. Applied physiology of soccer. *Sports medicine (Auckland, NZ).* 1986; 3(1):50–60. Epub 1986/01/01. <https://doi.org/10.2165/00007256-198603010-00005> PMID: 3633120.
39. Carling C, Bradley P, McCall A, Dupont G. Match-to-match variability in high-speed running activity in a professional soccer team. *J Sports Sci.* 2016; 34(24):2215–23. Epub 2016/05/05. <https://doi.org/10.1080/02640414.2016.1176228> PMID: 27144879.
40. Trewin J, Meylan C, Varley MC, Cronin J. The match-to-match variation of match-running in elite female soccer. *J Sci Med Sport.* 2018; 21(2):196–201. Epub 2017/06/10. <https://doi.org/10.1016/j.jsams.2017.05.009> PMID: 28595867.
41. Lacome M, Simpson BM, Cholley Y, Lambert P, Buchheit M. Small-Sided Games in Elite Soccer: Does One Size Fit All? *International journal of sports physiology and performance.* 2018; 13(5):568–76. Epub 2017/07/18. <https://doi.org/10.1123/ijsp.2017-0214> PMID: 28714774.

42. Silva P, Chung D, Carvalho T, Cardoso T, Davids K, Araujo D, et al. Practice effects on intra-team synergies in football teams. *Human movement science*. 2016; 46:39–51. Epub 2015/12/29. <https://doi.org/10.1016/j.humov.2015.11.017> PMID: 26707679.
43. Di Salvo V, Baron R, Tschan H, Calderon Montero FJ, Bachl N, Pigozzi F. Performance characteristics according to playing position in elite soccer. *Int J Sports Med*. 2007; 28(3):222–7. Epub 2006/10/07. <https://doi.org/10.1055/s-2006-924294> PMID: 17024626.
44. Mohr M, Krstrup P, Andersson H, Kirkendal D, Bangsbo J. Match activities of elite women soccer players at different performance levels. *J Strength Cond Res*. 2008; 22(2):341–9. Epub 2008/06/14. <https://doi.org/10.1519/JSC.0b013e318165fef6> PMID: 18550946.
45. Carling C, Bloomfield J, Nelsen L, Reilly T. The role of motion analysis in elite soccer: contemporary performance measurement techniques and work rate data. *Sports medicine (Auckland, NZ)*. 2008; 38(10):839–62. Epub 2008/09/23. <https://doi.org/10.2165/00007256-200838100-00004> PMID: 18803436.

# Paper 4

# Real-time Analysis of Physical Performance Parameters in Elite Soccer

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**Abstract**—Technology is having vast impact on the sports industry, and in particular soccer. All over the world, soccer teams are adapting digital information systems to quantify performance metrics. The goal is to assess strengths and weaknesses of individual players, training regimes, and play strategies; to improve performance and win games. However, most existing methods rely on post-game analytic, which restricts coaches to review games in retrospect, thus restricting them to implementing corrections to their team at some later time well after the corrections are mostly needed.

In collaboration with an elite soccer club, we have developed *Metrix*: a computerized toolkit for coaches to perform real-time monitoring and analysis of the players' performance. Using sensor technology to track movement, performance parameters are instantly available to coaches through a mobile phone client. *Metrix* provides coaches with a toolkit to individualize training load to different playing positions on the field, or to the player himself. Our results show that *Metrix* is able to quantify player performance and propagate it to coaches in real-time during a match or practice, i.e., latency is below 100 ms on the field. In our initial user evaluation, the coaches express that this is a valuable asset in day-to-day work.

**Keywords**—Athlete tracking; activity assessment; sport analysis; motion tracking; automated training assistance

## I. INTRODUCTION

Research in the last decade shows an increased demand on the physical performance of elite soccer players [1], indicating that the bar is continuously being raised as the sport evolves. Through technological advances in the use of quantified data and associated analytics, teams obtain valuable insight into performance metrics, serving as a foundation for evidence-based decisions regarding team improvements. The volume and immediate availability of such data allows coaches and sports scientists to make more informed decisions about current and future needs, i.e., optimizing the individual players' fitness and/or freshness and thereby increasing the teams' potential to perform.

Due to the non-linear flow of a soccer match, automated analysis is inherently difficult. There are already a lot of

parameters to consider during the game, and additionally, there are parameters like pre-game nutrition and post-game recovery that influence the performance. One commonly used approach is player-centric analysis, where teams collect large volumes of performance metrics regarding each individual player. Teams create extensive profiles on their players, holding information the coaches deem relevant for maintaining and increasing player performance. As data volume and complexity grow, efficient tools for automated high-precision retrieval become essential. However, data quantification methods mostly relies on post-game analytics, using automated or semi-automated tools to study performance metrics. This is often achieved through video based analysis tools or data captured by sensor devices [2]. Posterior evaluation is useful for hindsight notation, allowing coaches to apply corrections thereafter. Its weakness, however, is the lack of immediate feedback *during* matches and practice sessions, in situations that might require swift action from the coaches.

In this respect, we present the *Metrix* system providing live monitoring and analysis of player performance on the soccer field such that coaches can react to events in real-time. Parameters considered imperative by coaches are captured by our system and immediately made accessible through mobile devices or laptops operated on the field during match or training sessions. Experiments show that *Metrix* efficiently performs real-time analysis of players' position data captured using wearable sensors. *Metrix* is able to detect, process and propagate captured field-events with an end-to-end latency measured to be less than 100 ms with 25 players on the field, i.e., the system is able to provide real-time feedback to the coaches. Moreover, an initial user evaluation shows *Metrix* is useful for monitoring physical performance parameters and may have a positive impact on the individualization of physical training load, and coaches express they would like to use *Metrix* on a daily basis.



## II. METHODS

Metrix is a software system that provides soccer coaches with tools to quantify specific movement patterns of players, in relation to individual training goals and physical demands of different playing positions on the field. It is developed for and in close collaboration with coaches of an elite soccer club in Norway. The functionalities our system provides are implemented based on the coaches' specified requirements, and further customized to their needs.

Metrix is a web application, accessed by users through standard web browsers. We chose this interface technology and not an app so that the coaches can use any type of portable device, be it a phone, pad, tablet, PC, or even a big screen next to the soccer field.

Sensor data from the soccer field are captured and processed by the Metrix backend in real-time. The backend is responsible for parsing and analyzing sensor data, correlating it with physical performance parameters defined by coaches. Computed performance metrics are further distributed to connected clients through the frontend message manager. Users receive updates from field events through the Live Session interface in the client, implemented as a Single Page Application (SPA), which relies heavily on client-side scripting for serving the data in real-time.

### A. Data Sources

Our primary source of data is player movement during sport events (matches and trainings) using the ZXY Arena Sports Tracking system (ZXY) [3] from ChyronHego. ZXY is a highly accurate Local Position Measurement (LPM) system, based on the 2.45 GHz Industrial, Scientific and Medical (ISM) band radio signals from sensor belts worn by athletes to stationary receivers mounted around the stadium. The receivers are mounted in overlapping zones around the pitch to eliminate signal blocking and occlusion zones on the field. Each receiver independently computes the belt's position and trajectory on the field based on received signals. Our current setup uses a per belt sampling rate of 20 Hz, transmitting data records in real-time to a central relational database, which merges and stores all signals. The ZXY belts are also issued with accelerometers, a gyro, and a compass. Although Metrix can make use of traditional GPS based positional input sources, LPM systems generally provide better accuracy [4].

Prior to a match or training, coaches distribute sensor belts among the players and activate them through a designated ZXY subsystem. When a coach starts a new session, Metrix will connect to the ZXY Sensor stream, receiving raw sensor data records through a TCP connection. The output data records contain measurements from exactly one ZXY sensor belt. Belts are uniquely identified by a tag id, and each player wears exactly one belt.

Each ZXY data record is comprised of an array of sixteen unique data fields, measured by the sensor technology. The fields include positioning, direction, speed, etc. In our system, we need only concern ourselves with a subset of the data including the ID of the ZXY sensor belt, the local UNIX

timestamp, the current speed of the player, the current acceleration of the player, and the cumulative distance the player has moved so far. Metrix will parse the data records and further deserialize the content into internal data structures.

Note that the data is collected from player activities routinely measured during the competitive season. Therefore, a usual appropriate ethics committee clearance is not required [5]. Nevertheless, team and player confidentiality is ensured by anonymisation of all data, written informed consent from players and an approval from The Norwegian Centre for Research Data.

### B. Event Model

There are many types of interesting events and metrics that can be extracted from our sensor data. For this paper, we focus on two classes of movement data: run events and acceleration events. We count the number of occurrences of each event class and its duration in terms of distance covered.

1) *Run events*: A run event indicates movement of a player within certain speed zones. Metrix is configured to use two specific zones, both well established standards in the literature [6], [7]. A *High Intensity Run (HIR)* is a run at speed faster than  $5.5 \text{ m s}^{-1}$  over a time period greater than 1 s is said to be a HIR. A *sprint* A run at speed faster than  $7.0 \text{ m s}^{-1}$  over a time period greater than 1 s is said to be a sprint. Figure 1 shows an example recording of a typical run-event containing both HIRs and sprints as captured by Metrix. The run is characterized by the six markers A to F as follows:

- A** Start run: speed increases above  $4.0 \text{ m s}^{-1}$ .
- B** Start HIR: speed increases above  $5.5 \text{ m s}^{-1}$ .
- C** Start sprint: speed increases  $7.0 \text{ m s}^{-1}$ .
- D** End sprint: speed decreases below  $7.0 \text{ m s}^{-1}$ .
- E** End HIR: speed decreases below  $5.5 \text{ m s}^{-1}$ .
- F** End run: speed decreases below  $4.0 \text{ m s}^{-1}$ .

During event processing, Metrix captures the timestamps ( $t$ ) and cumulative distance covered ( $d$ ) from event markers A through F. The time from B to E asserts a valid HIR only if  $t_E - t_B > 1$ . If the run is valid, the time interval  $t_F - t_A$  defines the duration of the run, and the distance  $d_F - d_A$  defines the distance covered during the event. If the speed increases above  $7 \text{ m s}^{-1}$ , a valid HIR run becomes a sprint.

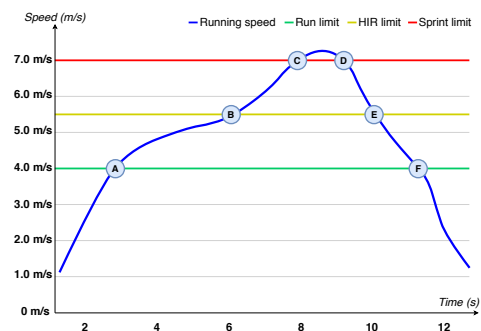


Fig. 1. Example of a run with different speed zones.



2) *Acceleration events*: The definition of an acceleration event is similar to the run event, but is derived from different sensor parameters. An *acceleration* is changes in speed of more than  $2.0 \text{ m s}^{-2}$  over a duration of 500ms. Figure 2 shows an example recording of the accelerations of a player as captured by Metrix. The captured acceleration events are defined by the following four markers:

- A** Start acceleration: acceleration increases above  $1.0 \text{ m s}^{-2}$ .
- B** Valid acceleration limit: acceleration increases above  $2.0 \text{ m s}^{-2}$ .
- C** Acceleration value decreases below the valid acceleration limit.
- D** End acceleration: acceleration decreases below  $1.0 \text{ m s}^{-2}$ .

Similar to runs, the property  $t_C - t_B > 0.5$  most hold for the event to be considered valid.

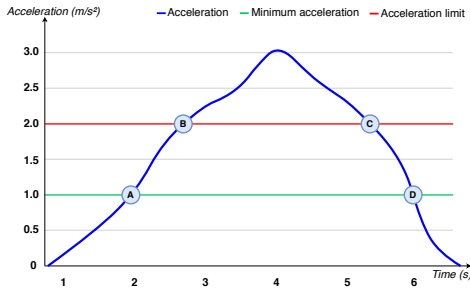


Fig. 2. Example of accelerations during a run.

### C. Data Processing Subsystem

Metrix includes a distributed data processing subsystem for analyzing sensor data and detecting on-field events. The data processing subsystem is designed with player analytics in mind. We apply the well-known controller-worker software pattern for this. Each active player in a session is therefore allocated its own worker process, responsible for processing all data records attributable to that particular player. Each worker is also allocated its own named job channel. The controlling orchestrator handles the detection and initialization of active players on the field. For performance reasons, player data is fetched and stored in memory for the duration of the on-going session, indexed through a map. Once a player has been identified, the orchestrator initiates a new worker assigned to that specific player.

Using per-player workers, Metrix improves concurrency, facilitating our requirement of serving player feedback in real-time. Assuming the server uses multiple cores, we achieve parallelism on a critical path in the data pipeline, ensuring low processing duration of field events. Assigning distinct worker routines to specific players in each session also provides a logical separation between processing tasks, reducing the need for synchronization and communication between worker threads as each worker only concerns itself with a unique subset of the data.

### D. User Interaction

Authenticated users are presented with several interfaces allowing them to interact with Metrix. Training sessions are scheduled intermediate of official matches. For professional soccer teams, this often involves recovery, followed by sessions focusing on technical tactical aspects and physical workout, often in a combination. Trainings are carefully planned and executed with regards to physical load and intensity. It is the coaches responsibility (and challenge) to find the balance between obtaining the desired training goals, and keeping the freshness of the players before an official match. Thus, there is a need to plan and monitor all activities. For example, a coach may require the central mid-fielders to achieve 70% of match-load over a period of four days. By quantifying specific load-intensive performance metrics, coaches can better monitor their players on a granular level. Players who are pushing themselves too close to the limit can be rested from specific drills, while those who are underloaded can receive additional physical load.

1) *Week Planner*: Metrix implements a Week Planner interface where coaches can set player-specific training goals within the current training period. The functionality of the Week Planner is primarily influenced and specified by the coaches involved in this project. As shown in Figure 3, our client displays a table of all the players in the team, as well as 0–100 percent adjustable sliders for each physical performance parameter we measure with Metrix. The percentage is calculated based on each player’s all-time best performance. For example, if a player’s highest value of sprint in an official match is 300 m, and coaches expects him to perform 50% of that during the week, his goal will be to achieve at least 150 m sprint. The initial best-performance values are gathered from historical match data, provided by the ZXY system. Submitted goals associated with the current training period are stored in the Metrix database, its values further used to portray the players goal on the progress bar during a live session, as we describe next.

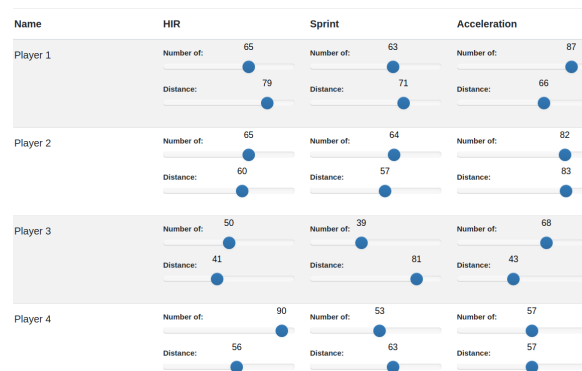


Fig. 3. Planning individual weekly training load (player names anonymized for privacy compliance).

2) *Live Session Cards*: To avoid exceeding planned workload of individual players, we use live session feedback. The

Metrix Live Session interface organizes player data in visual structures called *cards*, as show in Figure 4. There is one card for each player. A player’s card displays live data when he is participating in an on-going match or training session. The cards are updated in real-time in response to received data.

Each card is divided into a header and a body section. The card header contains the player’s name (1), sensor belt id (2), and a button (3) for listing detailed performance data from previous training sessions in the current week. Extra details are displayed in a popover, only visible through user interaction. The card body consists of six progress bars, visualizing number of conducted HIR (4), sprint and acceleration events, as well as distance covered during them. Progress bars display accumulated performance metrics from the entirety of the training week. A small marker on the bar (5) indicates the preset goal that coaches have set for the player for the current training period. The end of the progress bar (6) is defined by the player’s all-time best performance. Taking into account that the player may exceed this limit we also show the values explicitly with a label (7) in the center of the bar. The label show *accomplished value* out of *weekly goal* (e.g., 129 / 243 HIRs in the figure).

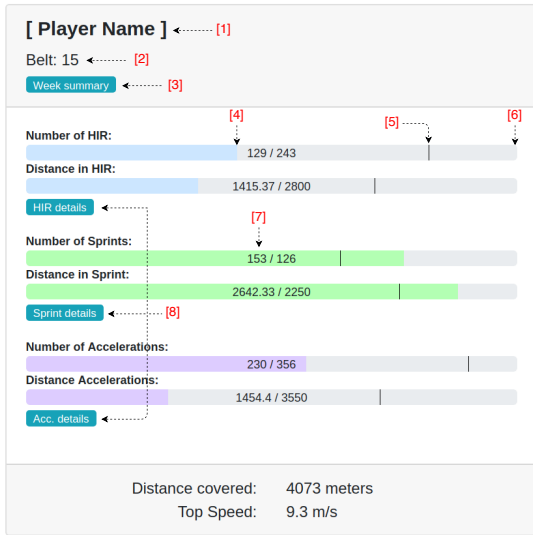


Fig. 4. Detailed view of a player card.

Users may request a detailed view of completed events by the click of a button (8). Detailed data is comprised of single events, arranged in a table, containing additional information on each of them. Event details are displayed in a popover, shown and hidden by user interactions. Figure 5 shows an example of a detailed view on completed sprints for a specific player. Each event in the detailed view is coupled with a button for playing a video of the performed event. When pressed, a video player will pop up and display the requested content.

Thus, based on these interfaces, the coaches can bring small devices onto the field and immediately see and take actions if particular players reach the planned load or if someone is underperforming.

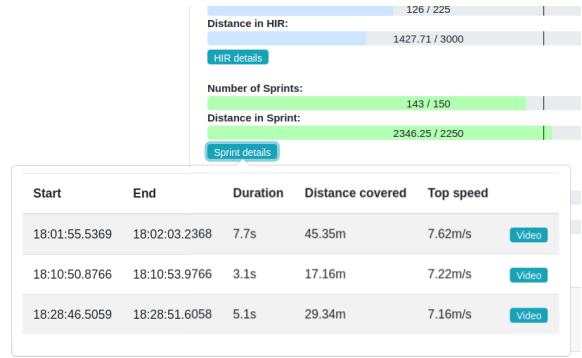


Fig. 5. Detailed view of session events (from Figure 4).

3) *Video Service*: The Metrix video service allows coaches to request video playback of player events during an on-going session (“Video”-button in Figure 5). As of today, the video component is conceptual, demonstrating that it is possible for real-time video playback of transpired events during trainings or matches. The service is based on the *Bagadus* [8] architecture, that records and stores video data on a daily basis. The video is stored in DASH-like segments, and video clips are described in manifest files generated on the fly based on the given timestamps of events, similar to the query methods described in [9]. Thus, the sensor data timestamps are matched to the corresponding video segments. These are included in the manifest, and video event playout is managed by the video player.

### III. EVALUATION AND RESULTS

To evaluate Metrix, we have performed several experiments. The following will describe our performance experiments on end-to-end latency, and our user satisfaction survey.

#### A. Analysis latency

The performance evaluation of Metrix concerns the systems capability of processing physical performance parameters and delivering the results in real-time. The sensor data input volume increases linearly with the number of players on the field, and our experiments therefore cover two realistic scenarios: an official match with 10 outfield players and a training session with 25 players in the squad. Additionally, we are interested in how our system scales with regards to an increasing number of coaches and other staff using Metrix simultaneously. In order not to affect the real running system, we have simulated sessions using real ZXY sensor data from a captured dataset [10]. As in the running system, the simulated ZXY server transmits data records at 20 Hz for 45 min (one period). For the 10 player experiment, there is a total of 221 events captured by Metrix, distributed among the players. In the 25 player experiment, we have duplicated some of the player data, resulting in a total of 525 captured events. Metrix is deployed on a desktop computer with an Intel Core i7-2600 processor, and the ZXY data server runs on an Intel Core i5-4200M workstation. All units use the same 1 Gbps network, consequently resulting in close to zero network latency.

Figure 6 shows the results of the end-to-end latency on captured events from the match. We observe that the average latency approximately doubles when increasing from 11 (Figure 6(a)) to 25 (Figure 6(b)) players, and the graphs show that the latency scales linearly with the increasing number of clients. Average latency during the 45 min session is below 100 ms, with both 11 and 25 players on the field, and up to 1000 clients using Metrix. In a typical use-case, with no more than two or three coaches using Metrix simultaneously, we have latencies (in the no delay network) of less than 10 ms.

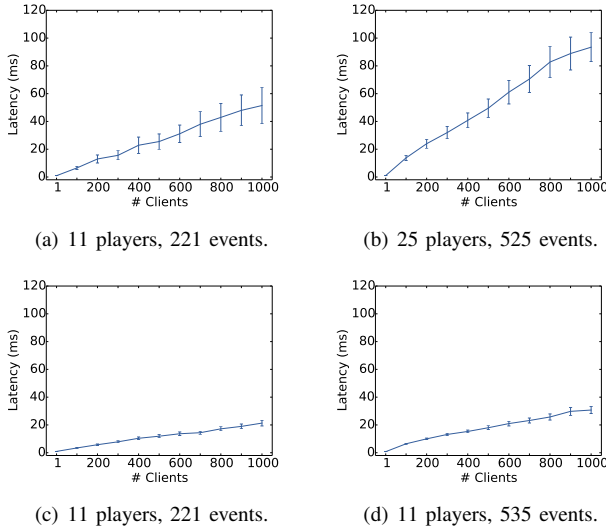


Fig. 6. End-to-end latency with 11 and 25 players. The error bars show the 95th-percentile confidence interval. In Figures (c) and (d), we have no 5-second periodic client update.

If the users do not need periodic updates, but rather want to query for the current status, we can observe in figures 6(c) and 6(d) that both the latency and the variance are greatly reduced, indicating that there is some significant overhead in the message manager (even though the experiment pushes updates to an unrealistic high number of users).

As our end-to-end latency is measured between devices operating on the same network, wide-area latency is not properly assessed through our experiments. In a real-world deployment, we expect the general latency to increase, depending on factors such as clients bandwidth or their proximity to the server. Nevertheless, the increased network latency is still in the area of 10 to 100 ms. This is considered sufficient for our purpose, as users are not expected to be able to react to feedback any quicker.

### B. User Evaluation

Metrix has been developed in collaboration with real end-users. A user survey is therefore an appropriate method to evaluate its value. However, since Metrix is only in pre-production use, we base our evaluation on a user-oriented presentation, involving an extensive demonstration of Metrix and its implemented features. The demo was followed by a questionnaire, evaluating Metrix by three main categories of

statements; functionality, design and overall interest in using Metrix (the questionnaire is available in [11]). Four coaches with experience from elite and the Norwegian national soccer teams participated, and rated the statements using a balanced 5-point Likert scale (i.e., using the response scale: strongly disagree, disagree, neutral, agree, or strongly agree).

The answers from the functionality questions Q1–Q6 in Figure 7 indicate that the assessors consider Metrix will improve objective monitoring of player load, and can be very useful to accomplish weekly training goals. The survey also indicates that the assessors were diverged on our question about Metrix enhancing the individualization of training programs during trainings (Q4). Some assessors strongly agreed, while others were neutral. We speculate that this variance might be rooted in how coaches prepare the training sessions in advance. For the design questions Q7–Q9 in Figure 7), the assessors agree that Metrix provides a user-friendly interface, where data is presented in an intuitive way. The assessors also said that the progress bars made player performance data easy to comprehend. Finally, the question Q11 shows the willingness to use such a system. In short, the assessors clearly believe Metrix can be impactful (Q10) for individual training load monitoring, and that it enhances coaches real-time intervention potential. All the assessors state that they would use Metrix on a daily basis if provided.

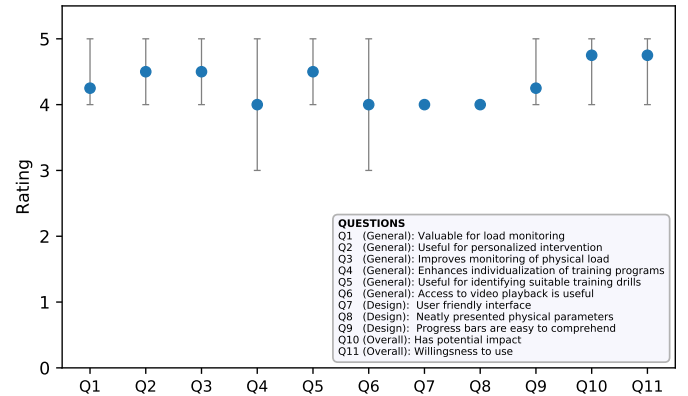


Fig. 7. User survey results for the different questions (Q) using a 5-point Likert scale.

## IV. DISCUSSION: QUANTIFYING AND ANALYZING SOCCER

Match analysis in soccer generally refers to the objective measurements and analysis of discrete events during training or competition [12]. Typical parameters include total distance covered, number of turns, and number of efforts performed in varying movement categories, i.e., jogging, running, sprinting [13], [14]. This information is used to develop extensive player activity profiles [15], outlining average physical demands of each player and their playing position on the field. Structured match analysis dates back to the 1970's [16], where coaches used *notational (pen and paper-based) analysis* to capture field events. An improvement to the classic notational analysis is *video-based time-motion analysis*,

involving players to be filmed during match or training [17]. Video footage is analyzed post-game, allowing observers to pause, review and slow down the videos for a closer look. With the advancements of digital technology, more semi-automated systems have replaced the manual approach of collecting player data. The perhaps most renowned system is ProZone [18], now called STATS, who in the early 2000's introduced a semi-automated video tracking solution using multiple cameras placed in fixed positions at the stadium, covering the entire field. In later years, commercially available GPS units designed for sports tracking have become increasingly popular for quantifying player performance metrics [19], [20]. The most renowned systems using this technology includes , GPSports [21], CatapultSports [22] and StatSports [23]. With advancements in GPS technology, the sensor components have decreased dramatically in size, now considered non-invasive for players to wear underneath their clothing during physical activity. Furthermore, another way to analyze the game is using video. Bagadus [8], [24] is a real-time sports analysis system providing instant video playback, but there is not automatic analysis of data involved.

In short, several approaches exist with different methods for collecting data. To the best of our knowledge, there are however few, if any at all, that actually perform analysis and give feedback in real-time allowing the coaches to act immediately. As a possible solution to fill the gap we present our Metrix system targeting real-time feedback based on the ZXY position sensor system [3] mentioned above.

## V. CONCLUSION

This paper describes Metrix, a novel cyber-physical system system that enables real-time monitoring of elite soccer players during matches and training sessions. In particular, Metrix provide real-time analysis of each individual player's position data, which is key to providing coaches with the toolkit they need to quantify specific movement patterns and analyze training loads in relation to preset training goals. Metrix also provides a method for coupling sports events with video recordings, allowing coaches to view replays of player-performed events.

Our evaluations show that Metrix efficiently performs real-time analysis of the ZXY sensor data, with an end-to-end latency to process and propagate captured field-events measured to be less than 100 ms with 25 players on the field. Our user evaluation shows that coaches find Metrix a highly useful tool for monitoring physical performance parameters and might have great impact on the individualization of physical training load. The questioned users express they would use Metrix on a daily basis if it has been available.

## REFERENCES

- [1] C. Barnes, D. Archer, M. Bush, R. Hogg, and P. Bradley, "The evolution of physical and technical performance parameters in the english premier league," *International Journal of Sports Medicine*, vol. 35, pp. 1–6, 2014.
- [2] H. D. Johansen, S. A. Pettersen, P. Halvorsen, and D. Johansen, "Combining video and player telemetry for evidence-based decisions in soccer," *Proc. of icSPORTS*, 2013.
- [3] ChyronHego, "Sports tracking - chyronhego," <https://chyronhego.com/products/sports-tracking>, 2018, [Online]. [Online]. Available: <https://chyronhego.com/products/sports-tracking>
- [4] S. A. Pettersen, H. D. Johansen, I. A. M. Baptista, P. Halvorsen, and D. Johansen, "Quantified soccer using positional data: A case study," *Frontiers in Physiology*, vol. 9, p. 866, 2018. [Online]. Available: <https://www.frontiersin.org/article/10.3389/fphys.2018.00866>
- [5] E. M. Winter and R. J. Maughan, "Requirements for ethics approvals," *Journal of Sports Sciences*, vol. 27, no. 10, pp. 985–985, 2009, pMID: 19847681.
- [6] E. Rampinini, A. Coutts, C. Castagna, R. Sassi, and F. Impellizzeri, "Variation in top level soccer match performance," *International journal of sports medicine*, vol. 28, no. 12, pp. 1018–1024, 2007.
- [7] P. S. Bradley, W. Sheldon, B. Wooster, P. Olsen, P. Boanas, and P. Krustup, "High-intensity running in english fa premier league soccer matches," *Journal of sports sciences*, vol. 27, no. 2, pp. 159–168, 2009.
- [8] P. Halvorsen, S. Sægrov, A. Mortensen, D. K. Kristensen, A. Eichhorn, M. Stenhaus, S. Dahl, H. K. Stensland, V. R. Gaddam, C. Griwodz *et al.*, "Bagadus: an integrated system for arena sports analytics: a soccer case study," in *Proceedings of the 4th ACM Multimedia Systems Conference*. ACM, 2013, pp. 48–59.
- [9] A. Mortensen, V. R. Gaddam, H. K. Stensland, C. Griwodz, D. Johansen, and P. Halvorsen, "Automatic event extraction and video summaries from soccer games," in *Proceedings of the ACM Multimedia Systems Conference (MMSYS)*. ACM, 2014, pp. 176–179.
- [10] S. A. Pettersen, D. Johansen, H. Johansen, V. Berg-Johansen, V. R. Gaddam, A. Mortensen, R. Langseth, C. Griwodz, H. K. Stensland, and P. Halvorsen, "Soccer video and player position dataset," in *Proceedings of the ACM Multimedia Systems Conference (MMSYS)*, 2014, pp. 18–23.
- [11] K. H. Andreassen, "Metrix: Real-time analysis of physical performance parameters in elite soccer," Masterthesis, University of Tromsø, 2018.
- [12] C. Carling, T. Reilly, and A. M. Williams, *Handbook of soccer match analysis: A systematic approach to improving performance*. Routledge, 2007.
- [13] W. R. Data, "The role of motion analysis in elite soccer," *Sports Med*, vol. 38, no. 10, pp. 839–862, 2008.
- [14] D. B. Dwyer and T. J. Gabbett, "Global positioning system data analysis: Velocity ranges and a new definition of sprinting for field sport athletes," *The Journal of Strength & Conditioning Research*, vol. 26, no. 3, pp. 818–824, 2012.
- [15] P. S. Bradley, M. Di Mascio, D. Peart, P. Olsen, and B. Sheldon, "High-intensity activity profiles of elite soccer players at different performance levels," *The Journal of Strength & Conditioning Research*, vol. 24, no. 9, pp. 2343–2351, 2010.
- [16] T. Reilly and V. Thomas, "A motion analysis of work rate in different positional roles in professional football match play," *J.HUM.MOVEMENT STUD.*, vol. 2, pp. 87–97, 01 1976.
- [17] J. Bangsbo, L. Nørregaard, and F. Thorsoe, "Activity profile of competition soccer," *Canadian journal of sport sciences= Journal canadien des sciences du sport*, vol. 16, no. 2, pp. 110–116, 1991.
- [18] STATS LLC, "Sports data company — sports technology, data feeds, content — stats," <https://www.stats.com>, 2018, [Online]. [Online]. Available: <https://www.stats.com>
- [19] M. Pentz, "Sounders among pioneers in mls with analytics, training," August 2015, [Online; posted 03-August-2015]. [Online]. Available: <https://www.seattletimes.com/sports/sounders/sounders-among-pioneers-in-mls-with-analytics-training/>
- [20] B. Wisbey, P. G. Montgomery, D. B. Pyne, and B. Rattray, "Quantifying movement demands of all football using gps tracking," *Journal of science and Medicine in Sport*, vol. 13, no. 5, pp. 531–536, 2010.
- [21] GPSports, "Gps tracking systems for elite sports — globally positioning sport since 2001," <http://gpsports.com>, 2018, [Online].
- [22] Catapult Sports, "World leader in sport technology for elite sports — catapult sports," <http://www.catapultsports.com>, 2018, [Online]. [Online]. Available: <http://www.catapultsports.com>
- [23] STATSports Group Limited, "Statsports — GPS player tracking and performance analysis," <http://www.statsports.com>, 2018, [Online]. [Online]. Available: <http://www.statsports.com>
- [24] H. K. Stensland, V. R. Gaddam, M. Tennøe, E. Helgedagsrud, M. Næss, H. K. Alstad, A. Mortensen, R. Langseth, S. Ljødal, Ø. Landsverk *et al.*, "Bagadus: An integrated real-time system for soccer analytics," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 10, no. 1s, p. 14, 2014.

# Paper 5

# **Positional differences on most demanding passages and accumulated training load relative to match load in elite football players**

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## Abstract

Quantification of training and match load is an important method to personalize the prescription of training stimulus to players, according to their match demands. The present study used time-motion analysis and triaxial-accelerometer to quantify and compare: a) the most demanding passages of play in training sessions and matches; b) and the accumulated load of typical training weeks (7 days-microcycles) and official matches, by playing position. Players performance data (18 outfield players) in 15 official home matches and 11 in-season microcycles was collected for analysis. Players were divided into four different playing positions: centre-backs (n=4; match observations [M<sub>obs</sub>]=42; training observations [T<sub>obs</sub>]=141), wing-backs (n=3; M<sub>obs</sub>=21; T<sub>obs</sub>=101), centre midfielders (n=5; M<sub>obs</sub>=40; T<sub>obs</sub>=162) and centre forwards (n=6; M<sub>obs</sub>=32; T<sub>obs</sub>=133). The results show that match demands were largely overperformed for acc<sub>counts</sub> (131-166%) and dec<sub>counts</sub> (108-134%), by all the playing positions. However, relative to match values, training values for sprint<sub>dist</sub> and HIR<sub>dist</sub> were considerably lower (36-61% and 57-71%) than for accelerations and decelerations. In relation to the 5-min peaks, the most pronounced difference was observed between playing positions in sprint<sub>peak</sub>, with WB achieving, during the microcycle peaks, only 64% of the most demanding 5-min sprinting in matches, while CB, CM and CF levelled and overperformed the match values (107%, 100% and 107%, respectively). Both under- and overloading may affect performance and increase the injury risk. Furthermore, differences observed across playing positions in matches and microcycles underline the importance of the individualisation of the physical training, within the collective periodization.

**Key-words:** external load; accelerations; high-intensity runs; sprints; match demands; microcycle; playing position

## Introduction

Objective data and time motion analysis are used by coaches and practitioners to characterize physical demands of training sessions and matches, allowing training load (TL) and training specificity analysis. This data may provide valuable information when designing and optimizing training programs (1). Besides, even though general physical demands of match play are well known, there is a great variation across playing positions (2, 3) and the position

specific load needs to be taken into consideration when designing and implementing training program cycles. Of particular importance is the potential ability that objective data provides for personalized prescription of TL in a cohort of players following the same overall training regime.

Several studies have focused on the match load (ML) of professional football players (4). However, in contrast to ML, information about the TL in elite players is scarce. Furthermore, important physical variables such as accelerations, decelerations and peaks of high-intensity runs and sprints have been neglected in some previous research. Managing TL according to the average ML of the team is not sufficient and new approaches are needed, in order to fulfil the law of training specificity (5). In fact, previous research (6, 7) has concluded that athletes become underprepared for the most demanding phases of play if their training programs only focus in replicating the average demands of competition. The need of a deeper understanding of ML, as the analysis of peaks of intensity according to playing position, is then fundamental to better prepare the athletes for the physical demands of competition.

Only recently, some studies have analysed the TL of professional football players and most of this research has paid special attention to the quantification of the TL in different microcycles (8, 9) and to the comparison of unequal sessions within the same microcycle (10-13), using the “match-day minus or match-day plus” (MD-; MD+) approach (14). The accumulated weekly TL relative to ML is still unclear since training and match are usually measured with different tracking systems (13), which raises challenges regarding the validity of comparisons. Previous research (13), have attempted to perform comparisons between TL and ML using the same tracking system. However, despite interesting results, only a few and non-official matches, with a different duration than official matches, were analysed.

To the best of our knowledge, this study was only the third study to compare weekly training demands with match demands, but the first taking into consideration the most demanding passages of play and the players playing positions while using official matches for comparison. The aims of the present study were to quantify and compare: a) the most demanding passages of play in training sessions and matches; b) the accumulated load of typical training weeks (7 days-microcycles) and official matches by playing position. We hypothesize that HIR and sprints will present considerably lower training/match ratios when compared to accelerations and decelerations, and that the most physically demanding playing positions in match will present lower training/match ratios than less demanding positions (mainly taking into considerations the overuse of small-sided games (SSG) and/or exercises played in relatively small areas in training sessions).



## **Methods**

### *Participants*

With approval from UiT The Arctic University of Norway Institutional Review Board, written informed consent from players and approval from Norwegian Centre for Research Data, 18 outfield football players from the first team (highest level) of a Norwegian elite club took part in the study. Data from 15 official home matches and 11 in-season microcycles was collected for analysis, and players divided into four different playing positions: centre-backs [CB] (n=4; match observations [ $M_{obs}$ ]=42; training observations [ $T_{obs}$ ]=141), wing-backs [WB] (n=3;  $M_{obs}$ =21;  $T_{obs}$ =101), centre midfielders [CM] (n=5;  $M_{obs}$ =40;  $T_{obs}$ =162) and centre forwards [CF] (n=6;  $M_{obs}$ =32;  $T_{obs}$ =133). These positions were chosen according to team's tactic formation (1-3-5-2) and previous research (3, 15, 16).

To ensure players confidentiality, all data was anonymized before analyses.

### *Procedures*

TL and ML data was collected using a stationary radio-based tracking system (ZXY Sport Tracking System, Trondheim Norway) – specifications bellow. Match activity profiles, per position, in 15 official home matches during the 2018 season were characterized. Match data (excluding the warm-up) was analysed only if: (a) players completed, at least 60 min of the match (13), and (b) the player played all the time in the same position. Match activity based on samples of less than 90 min were extrapolated to 90 min. We adapted the inclusive and extrapolation criteria from Stevens et al. (13), using the match data from players who played for at least 60 min. External load data of 11 typical microcycles (4 football training sessions within the 6 days-period between matches) was collected and analysed per position. Players without  $M_{obs}$  were not included in the sample, and  $T_{obs}$  from players who did not finish the training session were also excluded from analysis. All training sessions were composed by warming-up exercises and either combination of technical drills, football conditioning games (SSG), finishing drills and tactical exercises.

The team used in this study rarely played more than one match per week (participating only in the national league and cup). However, many breaks during the season (FIFA International Match Calendar, Summer break, etc.) led to a smaller number of “typical weeks” tracked (1 match per week with 6 full days between matches) (13, 17) than what was expected. These typical microcycles often included 2 days-off (MD+1 and MD-2) and 4 training sessions. Only

the main team sessions were considered. This refers to the training sessions where both starting and non-starting players trained together. Consequently, other types of sessions were excluded from analysis, including recovery sessions (MD+1), individual and conditioning training, as well as additional training for non-starters (MD+1).

The matches and training sessions were all played on the same artificial grass surface (Alfheim Stadium, Tromsø, length = 110m; width = 68m).

### *Data collection and data analysis*

Each player wore a specially designed belt, wrapped tightly around the waist, with an electronic sensor system at the player's lumbar spine. The accuracy and reliability of the system in measuring player movements in elite soccer competitions have been described in more detail in previous research (18).

Physical parameters analysed included: number of accelerations ( $\text{acc}_{\text{counts}}$ ), number of decelerations ( $\text{dec}_{\text{counts}}$ ), HIR distance ( $\text{HIR}_{\text{dist}}$ ), sprint distance ( $\text{sprint}_{\text{dist}}$ ), 5-min peak of accelerations ( $\text{acc}_{\text{peak}}$ ), 5-min peak of deceleration ( $\text{dec}_{\text{peak}}$ ), 5-min peak of HIR distance ( $\text{HIR}_{\text{peak}}$ ) and 5-min peak of sprint distance ( $\text{sprint}_{\text{peak}}$ ).

The following locomotor categories were selected: HIR ( $\geq 19.8 \text{ km}\cdot\text{h}^{-1}$ ) and sprinting ( $\geq 25.2 \text{ km}\cdot\text{h}^{-1}$ ). The speed thresholds applied for each locomotor category are similar to those reported in previous research (16, 19-21).

According to the ZXY Sport Tracking system, accelerations are defined by four event markers: (1) the start of the acceleration event is marked by the acceleration reaching the minimum limit of  $1 \text{ m}\cdot\text{s}^{-2}$ , (2) the acceleration reaches the acceleration limit of  $2 \text{ m}\cdot\text{s}^{-2}$ , (3) the acceleration remains above the  $2 \text{ m}\cdot\text{s}^{-2}$  for at least 0.5 seconds and (4) the duration of the acceleration ends when it decreases below the minimum acceleration limit ( $1 \text{ m}\cdot\text{s}^{-2}$ ).

### *Statistical analysis*

The results are presented as mean and standard deviation, unless otherwise stated. A linear mixed-effects model with restricted maximum likelihood estimations was used to examine differences in LPM-derived variables (sum or peak) between training and match by position. Mixed models can account for unbalanced repeats per player and thus used to model the data. The fixed effects in the models included session type, playing position and interaction term, while 'athlete ID' was included as a random effect. Thus, each athlete had a subject-specific intercept. An  $\alpha$ -level of 0.05 was used as level of significance for statistical comparisons.

Furthermore, multiple comparisons were adjusted using the Tukey method. The t statistics from the mixed models were converted to effect size correlations (22). Effect sizes were interpreted as <0.1, trivial; 0.1-0.3, small; 0.3-0.5, moderate; 0.5-0.7, large; 0.7-0.9, very large; 0.9-0.99, almost perfect; 1.0, perfect (23). All statistical analyses were conducted using the lm4, lsmeans and psychometric packages in the software r (24) were used for the analysis.

## Results

### *Accumulated training load*

CF was the only playing position which presented significant differences between matches and microcycles, in all the four variables analysed in Table 1. More accelerations and decelerations were performed during training sessions ( $112.3 \pm 5.8$  and  $94.1 \pm 5.9$ ) than in matches ( $78.5 \pm 6.2$  and  $74.3 \pm 6.3$ , respectively). Furthermore, the inverse was observed in HIR<sub>dist</sub> and sprint<sub>dist</sub>, with higher distances being covered during matches ( $897.1 \pm 62.6$  and  $171.7 \pm 1.0$ ) compared to trainings ( $561.0 \pm 59.3$  and  $104.6 \pm 0.9$ , respectively).

During the microcycles, CB accumulated significantly higher acc<sub>counts</sub> ( $89.0 \pm 6.0$ ) and dec<sub>counts</sub> ( $73.6 \pm 6.4$ ) than in matches ( $61.1 \pm 6.0$  and  $55.1 \pm 6.4$ , respectively). However, the opposite was observed regarding HIR<sub>dist</sub> and sprint<sub>dist</sub> performed in matches ( $479.5 \pm 65.9$  and  $86.3 \pm 1.0$ ) being considerably higher than in microcycles ( $340.7 \pm 65.8$ ;  $42.6 \pm 1.0$ , respectively).

Even though, WB didn't present significant differences in acc<sub>counts</sub> neither in dec<sub>counts</sub>, statistically lower values of HIR<sub>dist</sub> and sprint<sub>dist</sub> were observed in the microcycles ( $564.9 \pm 76.4$  and  $85.8 \pm 1.2$ ) than in matches ( $984.7 \pm 82.9$  and  $238.2 \pm 1.3$ , respectively).

Moreover, CM presented statistical differences between matches and microcycles only in acc<sub>counts</sub> ( $54.2 \pm 6.0$  and  $90.2 \pm 5.5$ ) and HIR<sub>dist</sub> ( $615.4 \pm 63.4$  and  $374.1 \pm 59.9$ , respectively).

Figure 1 shows the estimated cumulative load per variable during a microcycle expressed as a percentage of tracked match values (100%). As it can be observed, the match demands were largely overperformed for acc<sub>counts</sub> (131-166%) and dec<sub>counts</sub> (108-134%), by all the playing positions. However, relative to match values, training values for sprint<sub>dist</sub> and HIR<sub>dist</sub> were considerably lower (36-61% and 57-71%) than those previously reported for accelerations and decelerations.

### *Most demanding passages of play (5-min peaks)*

Significant differences between matches and trainings were observed only in acc<sub>peak</sub> of CB ( $6.4 \pm 0.4$  and  $7.5 \pm 0.4$ ) and CM ( $6.2 \pm 0.4$  and  $7.7 \pm 0.4$ , respectively) (Table 2). However, WB

presented slightly higher values of  $\text{HIR}_{\text{peak}}$  and  $\text{sprint}_{\text{peak}}$  in matches ( $119.0 \pm 9.6$  and  $56.7 \pm 6.7$ ) than in trainings ( $84.3 \pm 8.6$  and  $36.3 \pm 6.0$ , respectively). All the other playing positions and peak variables presented similar values between matches and microcycles.

Moreover, Figure 2 shows the estimated training 5-min peaks of the whole microcycle, expressed as a percentage of estimated match values (100%). For  $\text{acc}_{\text{peak}}$  and  $\text{dec}_{\text{peak}}$  the percentages did not differ largely between playing positions (range: 102-124% and 88-115%, respectively), with CB and CM performing slightly higher values (relative to their specific match demands) than WB and CF. However, the biggest difference observed between playing positions is for  $\text{sprint}_{\text{peak}}$ , with WB achieving, during the microcycles, only 64% of the most demanding 5-min sprinting in matches, while CB, CM and CF levelled and overperformed the match values (107%, 100% and 107%, respectively).

## Discussion

In the present study, we objectively quantified and compared, per playing position, the weekly training load and most demanding passages of play (5-min peaks) with match demands. Consistent with our hypothesis, the number of accelerations and decelerations during training weeks were considerably higher than the match values, while the distances ran at the most demanding speed thresholds (HIR and sprints) were much lower in microcycles than in matches. In general, the results reveal a lack of consistency between positions in the accumulated training load and in the most demanding 5-min peaks, relative to their specific match demands. Tables 1 and 2 reveal that while the training demands were statistically different than the match demands for some positions (e.g. CB and CF in  $\text{dec}_{\text{counts}}$ ), the same was not observed for other positions, where the differences between training and matches were insignificant (e.g. CM and WB in  $\text{dec}_{\text{counts}}$ ).

According to previous research (13, 17), the interpretation of training load data is facilitated when match load is used as a reference, helping the training prescription as well as the communication between coaches and players. Therefore, figures 1 and 2 show the estimated cumulative load and the 5-min peaks during a microcycle, expressed as a percentage of tracked match values (100%).

In fact, tables 1 and 2 present only the absolute values of several variables in trainings and matches, however, practical conclusions are difficult to extract from those values. On the other hand, Figure 1 clearly shows that match demands were overperformed for  $\text{acc}_{\text{counts}}$  (131-166%) and  $\text{dec}_{\text{counts}}$  (108-134%) but underperformed for HIR (57-71%) and sprints (36-61%). These

results are somewhat in line with previous studies with Dutch (13) and Portuguese (17) football teams, where similar discrepancies between the accumulated weekly load of different variables were reported. These findings suggest that nowadays, the training drills used tend to emphasize some physical variables, such as accelerations and decelerations, and neglect others, like HIR and sprints. Ade et al. (25) found that SSG and exercises played in small areas increased the number of accelerations and decelerations, when compared with running-based drills, but the latter requested more HIR and sprints. Gabbett et al. (26) also suggested that, since SSG do not simulate high-intensity and sprint demands of official matches, such exercises should be complemented with game-specific drills where the high-intensity and sprint demands of international competitions are represented.

Even though, the ability to perform high-intensity exercise has been proved to be strongly correlated with success in football (22, 27), some research in different collective sports, including football (28-31), defend that the concept of “train as you play” is highly impractical, due to the high match demands and the associated injury risk. Indeed, differences between microcycles and matches should be expected, given that simply reproducing match demands in trainings would oversimplify the complex process of develop elite players (29, 32). However, it is very unlikely that trainings with consistently lower distance covered in the most demanding speed thresholds, compared with competition, offer an optimal stimulus for players adaptation to the match demands (29). Moreover, the argument of risk of overtraining, used to not raise the frequency and distance run at high-speed thresholds during trainings, may be rebutted with the higher metabolic demands as well as the greater neural activation of the working muscles when performing accelerations, decelerations and changes of direction, compared to constant speed running (33-36).

In a study with a Spanish football team (7), the authors concluded that the physical demands of the most demanding passages of play are position-dependent. Therefore, developing training programs based only on absolute or average match values may limit specificity and underestimate the real demands of the most demanding passages of competition. Figure 2 shows that when taken into consideration only the most demanding 5 min, differences between variables were minimized and match values replicated in trainings. However, one exception can be spotted, with WB performing considerably lower values of  $\text{sprint}_{\text{peak}}$  (64%) and  $\text{HIR}_{\text{peak}}$  (71%) than the other positions, suggesting that the players in this playing position may not be prepared for the worst-case scenario in matches. The fact that WB were required to perform longer distances of HIR ( $119.0 \pm 9.6$ ) and sprints ( $56.7 \pm 6.7$ ) in matches than all the other positions, means that training stimulus for this playing position should be increased if coaches

and practitioners aim to prepare these players for extreme events that occur in matches. A higher level of training specificity is needed in order to meet the match demands of all playing-positions. Such specificity can be achieved through on-field training methods that aim to match or exceed the demands of competition in all the performance components (physical, tactical, technical and psychological) (37).

Despite the novelty and practical implications for football practitioners given by this study, some limitations must be considered. The common limitation within the literature, when studying professional and elite players (small sample size) was one of the challenges faced in this research, as well as the fact that only one team was analysed. This means that true differences might be masked due to a statistical type 2 error, and coach's training philosophy may also have contributed for differences observed. Another limitation, relates to one of the difficulties when using applied research, which was the fact that only 11 microcycles were tracked, since the team's match schedule and coach's decisions about the structure of the microcycle (microcycles with less or more than 4 training sessions) couldn't be controlled by the researchers. Nevertheless, this choice was made to ensure that precise values of the most common types of microcycles in elite football (4 training sessions) (9, 10, 13, 30, 38, 39) were obtained. Moreover, any internal load measures (e.g. hear-rate, RPE, etc.) were considered since it was out of the scope of this study. Finally, more specific comparisons with the results of previous research is difficult to conduct, since currently there is little consensus regarding the acceleration and deceleration thresholds used in team sports (40) and because of the different tracking systems used.

Future research should also attempt to better contextualize match loads, so practitioners can visualize the specific physical demands of different exercises. Nevertheless, the findings presented in this study provide important and novel information which may be used by practitioners to adapt their strategies to the need of a more position-specific training methodology.

### **Practical application**

The results presented, suggest that practitioners must carefully consider the physical work pattern of SSG's and other common football drills during microcycles to better resemble match performance and to avoid positional differences in the relative training load. Position-specific training is likely to appear if the players typically train in the same positions in which they will compete (37), and to do so, we recommend the use of bigger SSG (e.g. > 6vs6) in practices, as well as to complement these sessions with running-based drills. It is important to enhance that

there are many possible ways to achieve this type of specificity and we have only provided a few suggestions.

Coaches and practitioners, must keep in mind that the absolute TL accumulated by players of different positions should not be a tool for measurement. Alternatively, analysing the relative TL (according to the match demands) may be a much better and valuable way of managing and evaluating the players periodization. For instance, applying similar sprint distance, in trainings, to all the players, regardless their playing positions, would most likely lead to underloading WB and CF (most physically demanding positions) and overloading CB and CM (less physically demanding positions). Such differences are likely to affect performances and increase the injury risk. Furthermore, differences observed across playing positions in matches and microcycles underline the importance of the individualisation of the physical training, within the collective periodization.

Despite these novel findings, we acknowledge that these results are specific of one football team competing at the highest level in Norway. Even though, a number of contextual factors were considered, the findings are very likely specific to this group of players, playing style, training practices and type of periodization adopted by the coaching staff. Therefore, further research is needed to represent a broader overview of the relation between TL and ML in professional football as well as the effects of different periodization strategies. In addition, TL associated with individual practices, non-starters additional training sessions and recovery sessions should be taken into consideration in order to provide information about the additional load these practices provide to the players.

## References

1. Ade J, Fitzpatrick J, Bradley PS. High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. *J Sports Sci.* 2016;34(24):2205-14.
2. Bloomfield J, Polman R, O'Donoghue P. Physical Demands of Different Positions in FA Premier League Soccer. *Journal of sports science & medicine.* 2007;6(1):63-70.
3. Schuth G, Carr G, Barnes C, Carling C, Bradley PS. Positional interchanges influence the physical and technical match performance variables of elite soccer players. *J Sports Sci.* 2016;34(6):501-8.
4. Sarmiento H, Marcelino R, Anguera MT, CampaniCo J, Matos N, LeitAo JC. Match analysis in football: a systematic review. *J Sports Sci.* 2014;32(20):1831-43.
5. Small K, McNaughton L, Greig M, Lovell R. Effect of timing of eccentric hamstring strengthening exercises during soccer training: implications for muscle fatigability. *J Strength Cond Res.* 2009;23(4):1077-83.

6. Gabbett TJ. Influence of ball-in-play time on the activity profiles of rugby league match-play. *J Strength Cond Res.* 2015;29(3):716-21.
7. Martin-Garcia A, Casamichana D, Diaz AG, Cos F, Gabbett TJ. Positional Differences in the Most Demanding Passages of Play in Football Competition. *Journal of sports science & medicine.* 2018;17(4):563-70.
8. Jones RN, Greig M, Mawéné Y, Barrow J, Page RM. The influence of short-term fixture congestion on position specific match running performance and external loading patterns in English professional soccer. *Journal of Sports Sciences.* 2019;37(12):1338-46.
9. Oliveira R, Brito J, Martins A, Mendes B, Calvete F, Carrico S, et al. In-season training load quantification of one-, two- and three-game week schedules in a top European professional soccer team. *Physiol Behav.* 2019;201:146-56.
10. Coutinho D, Gonçalves B, Figueira B, Abade E, Marcelino R, Sampaio J. Typical weekly workload of under 15, under 17, and under 19 elite Portuguese football players. *Journal of Sports Sciences.* 2015;33(12):1229-37.
11. Martin-Garcia A, Gomez Diaz A, Bradley PS, Morera F, Casamichana D. Quantification of a Professional Football Team's External Load Using a Microcycle Structure. *J Strength Cond Res.* 2018;32(12):3511-8.
12. Martin-Lopez A, Mendes RS, Castillo-Rodriguez A. Internal and External Loads in Training Week Before the Competition in U19 High-Level Soccer Players. *J Strength Cond Res.* 2018.
13. Stevens TGA, de Ruiter CJ, Twisk JWR, Savelsbergh GJP, Beek PJ. Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players. *Science and Medicine in Football.* 2017;1(2):117-25.
14. Akenhead R, Harley JA, Tweddle SP. Examining the External Training Load of an English Premier League Football Team With Special Reference to Acceleration. *J Strength Cond Res.* 2016;30(9):2424-32.
15. Carling C, Le Gall F, Dupont G. Analysis of repeated high-intensity running performance in professional soccer. *J Sports Sci.* 2012;30(4):325-36.
16. Bradley P, Sheldon W, Wooster B, Olsen P, Boanas P, Krstrup P. High-intensity running in English FA Premier League soccer matches. *J Sports Sci.* 2009;27(2):159-68.
17. Clemente FM, Rabbani A, Conte D, Castillo D, Afonso J, Truman Clark CC, et al. Training/Match External Load Ratios in Professional Soccer Players: A Full-Season Study. *Int J Environ Res Public Health.* 2019;16(17).
18. Bendiksen M, Pettersen SA, Ingebrigtsen J, Randers MB, Brito J, Mohr M, et al. Application of the Copenhagen Soccer Test in high-level women players - locomotor activities, physiological response and sprint performance. *Human movement science.* 2013;32(6):1430-42.
19. Dalen T, Ingebrigtsen J, Ettema G, Hjelde GH, Wisloff U. Player Load, Acceleration, and Deceleration During Forty-Five Competitive Matches of Elite Soccer. *J Strength Cond Res.* 2016;30(2):351-9.
20. Ingebrigtsen J, Dalen T, Hjelde GH, Drust B, Wisloff U. Acceleration and sprint profiles of a professional elite football team in match play. *Eur J Sport Sci.* 2015;15(2):101-10.
21. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri FM. Variation in top level soccer match performance. *Int J Sports Med.* 2007;28(12):1018-24.
22. Krstrup P, Mohr M, Amstrup T, Rysgaard T, Johansen J, Steensberg A, et al. The yo-yo intermittent recovery test: physiological response, reliability, and validity. *Medicine and science in sports and exercise.* 2003;35(4):697-705.



23. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Medicine and science in sports and exercise*. 2009;41(1):3-13.
24. Team RC. A Language and Environment for Statistical Computing R Foundation for Statistical Computing, Vienna, Austria 2019 [Available from: <http://www.R-project.org/>].
25. Ade JD, Harley JA, Bradley PS. 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*. 2014;9(3):471-9.
26. Gabbett TJ, Mulvey MJ. Time-motion analysis of small-sided training games and competition in elite women soccer players. *J Strength Cond Res*. 2008;22(2):543-52.
27. Mohr M, Krstrup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci*. 2003;21(7):519-28.
28. Henderson B, Cook J, Kidgell DJ, Gastin PB. Game and Training Load Differences in Elite Junior Australian Football. *Journal of sports science & medicine*. 2015;14(3):494-500.
29. Higham DG, Pyne DB, Anson JM, Hopkins WG, Eddy A. Comparison of Activity Profiles and Physiological Demands Between International Rugby Sevens Matches and Training. *J Strength Cond Res*. 2016;30(5):1287-94.
30. Malone JJ, Di Michele R, Morgans R, Burgess D, Morton JP, Drust B. Seasonal training-load quantification in elite English premier league soccer players. *International journal of sports physiology and performance*. 2015;10(4):489-97.
31. Ritchie D, Hopkins WG, Buchheit M, Cordy J, Bartlett JD. Quantification of Training and Competition Load Across a Season in an Elite Australian Football Club. *International journal of sports physiology and performance*. 2016;11(4):474-9.
32. Duthie GM. A framework for the physical development of elite rugby union players. *International journal of sports physiology and performance*. 2006;1(1):2-13.
33. Akenhead R, French D, Thompson KG, Hayes PR. The physiological consequences of acceleration during shuttle running. *Int J Sports Med*. 2015;36(4):302-7.
34. Mero A, Komi PV. Force-, EMG-, and elasticity-velocity relationships at submaximal, maximal and supramaximal running speeds in sprinters. *Eur J Appl Physiol Occup Physiol*. 1986;55(5):553-61.
35. Mero A, Komi PV. Electromyographic activity in sprinting at speeds ranging from sub-maximal to supra-maximal. *Medicine and science in sports and exercise*. 1987;19(3):266-74.
36. Stevens TG, De Ruiter CJ, Van Maurik D, Van Lierop CJ, Savelsbergh GJ, Beek PJ. Measured and estimated energy cost of constant and shuttle running in soccer players. *Medicine and science in sports and exercise*. 2015;47(6):1219-24.
37. Gomez-Carmona CD, Gamonales JM, Pino-Ortega J, Ibanez SJ. Comparative Analysis of Load Profile between Small-Sided Games and Official Matches in Youth Soccer Players. *Sports (Basel, Switzerland)*. 2018;6(4).
38. Anderson L, Orme P, Di Michele R, Close GL, Morgans R, Drust B, et al. Quantification of training load during one-, two- and three-game week schedules in professional soccer players from the English Premier League: implications for carbohydrate periodisation. *J Sports Sci*. 2016;34(13):1250-9.
39. Los Arcos A, Mendez-Villanueva A, Martinez-Santos R. In-season training periodization of professional soccer players. *Biology of sport*. 2017;34(2):149-55.

40. Johnston RJ, Watsford ML, Pine MJ, Spurrs RW. Standardisation of Acceleration Zones in Professional Field Sport Athletes. *International Journal of Sports Science & Coaching*. 2014;9(5):1161-8.

