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Predicting Fatigue in Football Matches

Filipe Correia Ferreira

Dissertation submitted as partial requirement for the conferral of Business Analytics Master

Supervisor:

Assistant Professor Nuno Duarte Fialho Sanches Borges dos Santos, Department of Quantitative Methods for Management and Economics (IBS) ISCTE-Instituto Universitário de Lisboa

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Abstract

Football coaches must inevitably prepare their strategies not only for the upcoming match but also be prepared to restructure their strategies during the match itself. But there's more than that. The coach's duties extend beyond the four lines on weekends. The coach and his staff must plan a full week of training while considering everyone's current physical capabilities to avoid excessive fatigue or an injury that could prevent the player from being eligible to play for weeks. It is unquestionably in a coach's best interest to keep his players from being hurt or over-exhausted to the point where they are no longer suitable for the upcoming game. Fatigue or injuries are occurrences that can have a negative impact on every club stakeholder. Following investigations conducted by notable researchers like Bangsbo et al. (2006), Krustrup et al. (2010), Mohr et al. (2003), Rampini et al. (2009), Novak et al. (2021), and others, it was possible to achieve highly encouraging results that could actually be useful for coaches by providing them with knowledge of their players' degrees of fatigue in anticipation by developing a predictive model for three different time periods of anticipation (5-minutes; 10-minutes and 20-minutes) based on accurate monitoring of the players' GPS positions. Academically, it is believed that this work will open the door for more research initiatives of this kind as it was among the first, if not the first, to integrate real data to develop a realistic prediction model that could be used to evaluate fatigue.

Keywords: Physical performance; Player monitoring; Fatigue monitoring; Fatigue identification; Soccer; Football; Predictive models; Fatigue prediction; GPS tracking; GPS positioning;

JEL Classification: (C38) Classification Methods; Cluster Analysis; Principal Components; Factor Models, (C53) Forecasting and Prediction Methods; Simulation Methods, (Z20) General;

Resumo

Os treinadores de futebol devem inevitavelmente preparar as suas estratégias não apenas para o próximo jogo, mas também estar preparados para redesenhar as mesmas durante a própria partida. Mas há mais do que isso. As funções do treinador vão para além das quatro linhas ao fim-de-semana. O treinador e o seu staff devem planear uma semana inteira de treinos, considerando as capacidades físicas, atuais, dos jogadores, com o objetivo de evitar fadiga excessiva ou lesões que possam impedir os jogadores de ser opção para jogar durante semanas. É inquestionavelmente do interesse de um treinador evitar que os seus jogadores se lesionem ou fiquem fatigados ao ponto de não serem opções válidas para o próximo jogo. Fadiga ou lesões são ocorrências que podem ter impacto negativo em todos os stakeholders do clube. Suportado em investigações conduzidas por investigadores notáveis como Bangsbo et al. (2006), Krustrup et al. (2010), Mohr et al. (2003), Rampini et al. (2009), Novak et al. (2021), e outros, foi possível obter resultados altamente encorajadores que podem ser realmente úteis para os treinadores, possibilitando fornecer informação relativamente ao grau de fadiga dos jogadores antecipadamente, através de um modelo preditivo desenvolvido para três diferentes períodos (5-minutos; 10-minutos e 20-minutos) com base na monitorização nas coordenadas GPS. Academicamente, acredita-se que este trabalho poderá abrir portas para mais iniciativas de pesquisa no âmbito, dado que foi uma das primeiras, se não a primeira, a integrar dados reais para desenvolver um modelo preditivo realista que pode ser usado para classificar fadiga.

Palavras-Chave: Performance física; Monitorização de atletas; Monitorização de fadiga; Identificação de fadiga Futebol; Modelos preditivos; Previsão de fadiga; Rastreamento por GPS; Posicionamento GPS;

Classificação JEL: (C38) Métodos de Classificação; Análise de Conjuntos; Componentes Principais; Modelos Fatoriais, (C53) Métodos de Previsão; Métodos de Simulação, (Z20) Geral

Index

Table Index

Figure Index

List of abbreviations

Km/h – Kilometres per hour

U13 – Under 13 years

U14 – Under 14 years

U15 – Under 15 years

U16 – Under 16 years

U17 – Under 17 years

U18 – Under 18 years

GPS – Global positioning system

TDB – Total distance with the ball

HIRB – High-intensity running with the ball

HR – Heart rate

RPE – Rating of perceived exertion

ACL – Anterior cruciate ligament

POMS – Profile of mood states

REST-Q Sport – The recovery-stress questionnaire for athletes

DALDA – Daily analysis of life demands for athletes

TQR – Total recovery scale

sRPE – Session rating of perceived exertion

THIR distance – Total high-intensity running distance

CMJ – Countermovement jump

SJ – Squat jump

SP – Sprint performance

CK – Creatine kinase

WCS – Worst case scenario

Min – Minute

TD – Total distance

Vpeak – Peak velocity

M – Meters

OR – Odds ratio

RR – Relative risk

IRR – Incidence rate ratio

AUC – Area under the curve

PPV – Positive predictive value

NPV – Negative predictive value

ROC – Receiver operating characteristic

CRISP-DM – Cross industry standard process for data mining

.csv – Comma-separated values

M/s – meters per second

ETL – Extract, transform and load

GK – Goalkeeper

FB – Fullback

CB – Centre-back

MID – Midfielder

W – Winger

ST – Striker

CV – Coefficient of variation

Dist_HSR – Distance in high-speed running

Dist_SP – Distance in sprint

SP – Sprint

HSR – High-speed running

PCA – Principal component analysis

Chapter 1.

INTRODUCTION

1.1. Problem contextualization

Similar to all other businesses, it is imperative for the sports industry, in this context the football industry, in particular, to keep up with technological advancements such as the mass generation of data and its exploitation. The use of data science in football is still in its early stages, especially in the match component since, for instance, at the corporate level, it does not differ much from the others. Therefore, research in the area of data science applied to football becomes particularly important, especially at a time when it is getting easier to generate data other than the typical game statistics (shots, ball possession, corners, etc.). The growing use of GPS devices in athletes enables the generation of other types of data, such as the average positions or clinical data of the player during a match, in very high volumes.

According to Julian et al. (2021), due to the rising commercialization of the sport and growth in domestic and international cup events, fixture congestion is a common and current problem in professional soccer. Soccer clubs are frequently playing between 50 and 80 games in a season, especially high-level teams who participate in more competitions and achieve greater success in those, and this has been brought up in public by some of these players. Top-tier clubs in Europe, typically, begin their regular-season matches in August and wrap them up by the end of May or the start of June, however, some players will prolong their seasons to attend matches for their national teams, especially when there are Euros or World Cups. During a 300-day season, a player who participates in 60 matches for his club, plays approximately every 5 days, only at the club level. This focuses primarily on what is regarded as top-tier football, the major European leagues, and their national teams. It becomes even worse in Brazil. In 2020, Sociedade Esportiva Palmeiras played 77 games, having their goalkeeper starting in 66 of them. He also played in 2 games for his country, but this number could be higher given that he isn't a regular member of the national team.

Match-play congestion is likely to expose players to an increased level of fatigue and injury risk, according to Bengtsson et al. (2013), demanding a continual necessity for coaches to manage their players according to their level of fatigue and/or injury risk.

1.2. Study relevance and research questions

Once the prior notion has been presented, it becomes clear that football coaches must necessarily plan their strategies not just for the upcoming match, but also during the match itself. There is more, however. Beyond the four lines during the weekend, the coach's responsibilities are wide. In order to prevent excessive fatigue that could prevent a player from playing the next match or, worse yet, an injury that could prevent the player from being eligible to play for weeks, the coach and his staff must plan a full week of training during the week while considering everyone's current physical capabilities. It is undoubtedly in a coach's best interest to prevent his best players, or any players, from becoming injured or too fatigued to the point that they are no longer a valuable asset for the next match. When studying 40 different English football clubs over the course of 20 years, Szymanski & Kuypers (1999) discovered a correlation between sports results and club profits. The relevant link discovered by Barajas et al. (2005) indicates that an increase in revenue levels enables the club to sign more talented players the following season, leading to improved sportive performance. After analysing the Italian championship, Lago et al. (2004) concluded that there is a continuous cycle between sporting performances and financial resources, as it is necessary to sign quality players to put on a strong sporting display, which will then increase the club's power and competitiveness by bringing in more money, sponsors, and fans. Ultimately, sporting success and financial success is crucial for every professional club. Given this, it is possible that fatigue or injury might have a negative effect on all participants involved in the club.

Injury can arise from a variety of conditions, but as Luís (2021) pointed out, one of them is inadequate fatigue management (Tavares et al., 2017). This link between fatigue and injury makes it even more critical for coaches to adopt the best fatigue management they can.

However, how can coaches and their staff evaluate whether or not they are managing their players' fatigue effectively? Since there isn't a widely accepted fatigue marker identified in the literature, how can they determine the levels of fatigue?

This leads to the research questions for this dissertation:

1) Is it possible to establish a definition variable of fatigue?
2) And if it does, can it be predicted?

By being able to answer the proposed research questions, this dissertation may prove to be a beneficial tool for coaches in that they will be able to re-evaluate their training and match approaches to prevent fatigue and/or injuries. Academically, it could also bring up fresh perspectives or prospects for future research.

1.3. Research goals

Given the presented research question, the primary goals of this dissertation are:

O1) Explore multiple variables in order to establish a variable that may be used to characterize fatigue.

O2) Create a predictive model for different forecasting horizons to support coaches in anticipating and controlling fatigue.

In order to achieve these two main objectives, more specific objectives are proposed:

O1.1) Identify correlations between different external load variables.

O1.2) Investigate external load variations that could be compared to fatigue-related patterns.

O2.1) Examine training and match fatigue variations to assess if the former is consistent with what is intended in the latter.

O2.2) Since fatigue increases over time, assess whether fatigue from earlier training sessions may affect fatigue during a match.

The fulfilment of the objectives and, as a consequence, the response to the research questions, on the one hand, contribute to the literature by proposing a variable that can measure fatigue and perhaps overcome a knowledge gap. However, for those who work in the field, such as coaches and their staff, this study enables them to more accurately predict and track fatigue, it might even be beneficial to prevent injuries. As a result, it helps with more effective fatigue management, which could let teams to higher sportive success.

1.4. Methodological approach

Considering the objectives and the fact that it is built on real data, the research presupposes a quantitative approach.

The premise that a Portuguese professional football team is supporting this dissertation itself demonstrates its relevance. Although the use of the data was authorized to achieve the purpose defined in this research, there is a confidentiality agreement that assumes the anonymity of the data.

An intensive effort was made to establish the state of the art concerning important elements to answer the research question after reaching an agreement with a data provider and research sponsor. The chapter Literature Review resulted from this effort. Following a well-thought-out structure, the literature review explores first place Football match and fatigue patterns in order to comprehend what fatigue is and how it expresses; Following, Fatigue Monitoring examines if and how fatigue is assessed across multiple baselines and explores various methods from the literature; Then different fatigue markers proposed in the literature are evaluated via Self-Report Questionnaires, Performance Tests and Biochemical Measurements; Also an important topic for this research, GPS validity and reliability are investigated; Finally, to understand the discrepancies between this suggested dissertation and what has been accomplished in the literature, Association vs. Prediction helps clarify the variations between association and prediction.

After the Literature Review, the data gathered for this dissertation is presented, together with the data preparation methods used and some statistical description of the data. Consequently, once all the information has been gathered and compiled in line with the objectives of this study the modelling process is carried out and results are evaluated. The idea for this investigation's implementation follows immediately. Finally, conclusions, future work and limitations are presented.

1.5. Study structure and organization

In order to understand how to define fatigue, we have structured this work into seven chapters that comply with the different phases of the investigation.

This first section covers the contextualization of the problem and the research topic, outlining the goals and key contributions. The second chapter reflects the conceptual framework, referred to as the literature review, where several complex concepts are defined as well as various approaches found in the literature that were useful in order to better understand fatigue and what are the issues or what is lacking so that there can be a definition of it. The methodology used in this dissertation is outlined in chapter three, which also includes all the statistical methods applied to the data collection, processing and analysis phases. The fourth chapter discusses the modelling process. In the fifth chapter, the results obtained are presented and discussed. Deployment suggestions, conclusions, recognised limitations, and prospective research areas are provided in the end.

Chapter 2.

LITERATURE REVIEW

2.1 Football match and fatigue patterns

Football is probably the most popular sport in the world and is played professionally in nearly every country. This professionalization of football has demanded the need to develop all the industries and segments around it. Just like ordinary people, footballers are evaluated and broken down by their performance in their jobs so it is in their best interest to ensure they play at the expected level so their teams can achieve season goals. A player's performance is difficult to measure since it depends on a variety of abilities, faculties for making decisions and physical traits that may affect the previous ones. Additionally, a player's motions or skills may be restricted by a coach on a specific occasion (Buchheit et al., 2010; Mohr et al., 2010). Finding a tool that can assess performance overall is challenging. Nevertheless, it is widely recognized that a physical component plays a crucial role in an athlete's performance, therefore keeping an eye on fatigue and potential injuries is key. Injuries usually prevent the athlete from competing for a period of time, while fatigue is thought to impair their capacity to carry out their duties in the best possible physical condition (Thorpe et al., 2015). Fatigue is a complicated and diverse phenomenon that may be associated with several different causes. There are numerous definitions of fatigue. Supporting Halson (2014), "failure to maintain the required or expected force (or power output)" (Edwards, R. H. T., 1983) is one of the most popular definitions of fatigue. According to Taylor et al. (2012), fatigue is characterized as "a reduced capacity for maximal performance" (Knicker et al., 2011) which validates the earlier premise. During a football match, specific trends concerning the athletes' physical condition were identified, including that a match's second half usually has less distance covered than its first half (Reilly, 1997). However, instead of emphasizing solely the distance covered, football is distinguished by repeated, quick and intense activities such as accelerations and decelerations, the physiological implications of which repercussions cannot be overlooked. Several categories are usually used to describe the exertion and intensity of running, such as standing [from 0–2 km/h], walking [from 2–7 km/h], jogging [from 7–9 km/h], low-speed running [from 9–13 km/h], moderate-speed running [from 13–16 km/h], high-speed running [from 16–22 km/h], or sprinting [> 22 km/h] (Bangsbo et al., 1991; Mohr et al., 2003;

Rampinini et al., 2007; Casamichana et al., 2013; Buchheit et al., 2010; Twist et al., 2013). Even though any author may change the categories' thresholds or identifiers. Whatever the criteria or the names of the categories, it is evident that during the first half of the match, sprinting speed is higher, and throughout the second, it significantly decreases. (Mohr et al., 2003, 2008, 2010; Krustrup et al., 2010; Rampinini et al., 2009). Also, the ability to perform high-intensity running declines at the end of the game (Bangsbo et al., 2005, 2006). According to Rampinini et al. (2009) also "some technical skills decrease between the first and second half of official matches", particularly the frequency of ball touches, the number of short passes and the short passes success rate. The typical values for the distance covered in a single match, according to Bangsbo et al. (2006), are between 10 and 13 kilometres, and an 8 to 12 kilometres interval, according to Reilly (1997). The research conducted by Bangsbo et al. (2006) was conducted with elite-level football players, while Reilly's (1997) did not define the athletes investigated, which could explain the disparity. Also, football is becoming a more physically demanding sport due to fixture congestion as per Julian et al. (2021), therefore the fact that the research by Bangsbo et al. (2006) is more recent can be a differentiator. Another notable finding is the association between physical performance and playing positions, which made it possible to recognise some patterns according to the playing position. Players are typically categorised into one of five positions in the literature on the subject: central defenders, fullbacks, midfielders, wingers, or attackers. According to authors like Buchheit et al. (2010), Rampinini et al. (2007), and Bangsbo et al. (2006), central defenders cover less distance and perform less high-intensity running than players in other positions. When opposed to midfielders, fullbacks typically travel a shorter distance while maintaining a considerable distance at high-intensity. Midfielders typically run the most distance of all and the most distance at high-intensity although attackers sprint more often, which usually leads to a more marked decline in sprinting than midfielders or fullbacks. However, as per other investigations, there are additional variables, such as age, gender, and even the teams' skill level, that affect athletes' physical performance in addition to their playing positions. According to Buchheit et al. (2010), younger players cover less distance and sprint less during a match than older players do, according to an experiment done on teams of U13, U14, U15, U16, U17, and U18. The most extreme age groups showed the greatest disparities, with, for instance, minimal difference between U17 and U18. However, the previous trends such as the decline in physical markers from the first to the second half and the playing position patterns persist. Regarding the disparities between genders, Krustrup et al. (2010) supported the previously noted trends but emphasised that the impact on female players' physical conditions is greater than that reported for male players.

When assessing the link between team success levels, it was shown by Rampini et al. (2009) that less successful teams sprint and run substantially longer distances in general and at higher intensities than their more successful counterparts. In contrast, more successful teams cover a greater distance with the ball (TDB) and high-intensity running with the ball (HIRB) than less successful rivals. At last, the atmospheric conditions have repercussions on athletes' physical performance. Particularly in the heat, the distances covered and running intensity reduce, and fatigue is more noticeable than it would be in matches held in normal circumstances, this concept is validated by Drust et al. (2005), Reilly et al. (2008), Mohr et al. (2010, 2012), Buchheit et al. (2013).

It is clear from the prior works that the patterns observed—such as the physical decline towards the end of matches—are caused by fatigue, "although the potential influence of psychological and/or tactical factors should also be considered" (Mohr et al., 2010). Fatigue will therefore be defined for the purposes of this investigation as "an inability to perform a task that was once doable within a recent time range" (Pyne et al., 2011).

2.2. Fatigue Monitoring

Before even beginning to realize why and how monitoring fatigue is carried out, it is vital to comprehend a few technical terms used by experts in the field, such as the distinction between internal and external load and the relevance of this. Starting with external load, accordingly to Jaspers et al. (2018) is defined as “all player’s locomotor movements and can be measured using electronic tracking systems such as global positioning systems (GPS) and accelerometers. The external load is quantified in terms of distance, velocity and accelerations.” in other words, “External Load is defined as the work completed by an athlete measured independently of his or her internal characteristics” (Wallace et al., 2009) whereas internal load refers to players' physiological responses to an external load and is typically measured using heart rate (HR) and ratings of perceived exertions (RPE).

As players in professional football are often required to compete on a weekly and even biweekly basis, coaches and sports scientists have meticulously balanced training intensity and recovery. As per Halson (2014), variations in performance can be statistically discussed by monitoring workload. This can help reduce the level of uncertainty surrounding the adjustments and enhance its confidence regarding potential causes for changes in performance. Such data not only allows for the analysis of load-performance links in the past but also for the proper planning of training loads and competitions. Halson (2014) also shares the idea that load monitoring is used to try to lower the risk of injury, and fatigue overreaching. Data may also help choose a squad and identify athletes who are prepared for the challenges of competition. It's pertinent to find the right balance between workloads since both insufficient and excessive loading—which, according to Nimmo et al. (2007), can happen as a result of overtraining—can prevent performance improvement over the medium to long term by building up muscle stress and fatigue. "Determining the optimal balance between training load and recovery contributes to peak performance in well-trained athletes" (Lamberts et al., 2010). Additionally, it's crucial to highlight that anterior cruciate ligament (ACL) injuries are among the injuries that have been strongly associated with fatigue which typically forces the athlete to a long time period of recovery. ACL non-contact injuries have been reported in research findings to occur more commonly during matches than in practice, as well as nearer the conclusion of competitions and seasons, suggesting a cumulative impact of fatigue (Liederbach et al., 2014).

The management of fatigue is a critical component of sports performance since it will compromise training and performance, some authors have investigated how professionals monitor fatigue and the driving factors behind all this. Taylor et al. (2012) explored fatigue monitoring by interviewing a substantial number (100 individuals) of experienced professionals in the area. Their response rate (55%) allowed them to conclude some noteworthy findings: 91% of respondents implemented some form of a training monitoring system and the majority of respondents (70%) stated that their system places an equal emphasis on measuring load and monitoring fatigue and recovery. When asked what their main motivation was for using such a system, the responses were as follows: injury prevention (29%), monitoring the effectiveness of the training program (27%), maintaining performance (22%), and preventing overtraining (22%) and relative to the added value of their monitoring system, 38% rated it as extremely valuable, with a mean response of 3.9 ± 1.1 on a 5-point scale (1 = minimal value; 5 = extremely valuable). It is evident that professionals believe favourably in such a system and the benefits it offers. Self-report questionnaires were the most popular way of identifying fatigue response to training and competition (84%) with 11 respondents relying exclusively on self-reported metrics in their monitoring systems. Moreover, 61% of the respondents stated that they employ some form of performance test as part of their monitoring system. Jump tests (54%) are the most popular, followed by sport-specific test protocols (20%) and strength tests (16%). Restricting responses to only those made by football-experienced professionals, the most popular performance tests were jump tests followed by sport-specific test protocol, overground sprint tests and submaximal running. Besides self-report questionnaires and performance tests, a good approach for monitoring fatigue and recovery in football was performance monitoring during athletic competition. The use of GPS as a quantifier for physical metrics was reported by every single person involved in monitoring fatigue during athletic activity. The most often reported GPS metrics were meters per minute, time spent in high-intensity (Abt et al., 2009) and overall distance (Jaspers et al., 2018; Akubat et al., 2012), however many other factors were also stated, such as the coach's evaluation of performance, the number of tackles made, and other game data. Also, four responses indicated the use of biochemical monitoring for assessing fatigue. In summary, self-report questionnaires, performance tests, and biochemical indicators are the three most popular ways to monitor fatigue.

By exposing players to extremely difficult training to get them prepared for the physical demands of competition, particularly the worst passages of play, sports scientists hope to build endurance in their athletes. In fact, fatigue monitoring is relevant in this context to ensure that players are subjected to the appropriate level of external load—neither too much nor too little.

As per Robson-Ansley et al. (2009), “Fatigue is often a consequence of physical training and the effective management of fatigue by the coach and athlete is essential in optimizing adaptation and performance.”

2.3. Self-Report Questionnaires, Performance Tests and Biochemical Measurements and other approaches

According to Taylor et al. (2012), self-report questionnaires, performance tests, and biochemical measurements are among the most popular methods for evaluating fatigue, emphasizing that a clear and accurate fatigue marker has not yet been established.

The training load and subsequent reactions may be determined relatively efficiently and economically with questionnaires. There are a few questionnaires that have been documented in the literature and are used by professionals, such as the Profile of Mood States (POMS) (Morgan et al. 1987), The Recovery-Stress Questionnaire for athletes (REST-Q Sport) (Kellmann et al. 2000), Daily Analysis of Life Demands for Athletes (DALDA) (Rushall, 1990), the Total Recovery Scale (TQR) (Kenttä et al. 1998) and the Rating of Perceived Exertion (RPE) (Borresen et al. 2009). Self-report questionnaires are based on the assumption that athletes can effectively monitor the stress responses their bodies are under while they are engaged in physical activity. There is evidence to substantiate the association between RPE and heart rate (Borresen et al. 2009). Foster (1998) developed a novel method, session-RPE (sRPE), for measuring training load based on RPE, which requires multiplying the athlete's RPE by the length of the session (in minutes). The quality and accuracy of this method were solid and correlated well with heart rate. The perceived level of exertion among the players and the daily variation in THIR distance was found to be moderate to strongly correlated by Thorpe et al. (2015). According to the regression model's curve, RPE decreased by one unit for every (approximately) 400-meter increase in THIR distance (Thorpe et al., 2017). In short, questionnaire-based methods can detect functional overreaching in athletes because it has been demonstrated that they are affected before declines in performance is seen. The upsides of subjective measures are established as relevant: simple, easy to use, well-rated in the literature and cost-effective. However, there are uncertainties and gaps that need to be considered. As per Borresen et al. (2008), these methods act more as a general indicator of how demanding a session or match was for athletes. Akenhead et al. (2016) add that RPE after a competition may be influenced by match outcome, psychological states of the players, hormones and neurotransmitter levels or other contextual variables (crowds). Besides that, according to Twist et al. (2013), given its subjective nature, it can be easily manipulated. This could be a concern, particularly in team sports, athletes could be reluctant to confess exhaustion because doing so might prevent their selection for the upcoming matches.

Performance tests are far less of a subjective measure. To assess fatigue, performance tests include submaximal and maximum performance demands. Different performance evaluations exist, such as the Countermovement Jump (CMJ), Squat Jump (SJ), Yo-Yo IR1, the Intermittent Fitness Test (30-15) and the Sprint Performance (SP). These tests' objectivity is one of their strengths. Allows the identification of performance capacity and fatigue following a match or training session. Yet, there are still some questionable aspects taken into consideration. These tests are time-consuming, technique variability can induce different outcomes and can induce additional fatigue in athletes and, last but not least, they are post-event evaluations. Ineffective for high-frequency prediction during matches, but effective for diagnosis and explanation. Furthermore, Twist et al. (2013) emphasize that some performance evaluations performed in the literature have drawn criticism for not being sport-specific and, as a result, lacking to replicate the physical demands or movements of that sport. In Thorpe et al. (2015), the findings revealed that daily CMJ monitoring provides just a limited amount of information about the level of recovery fatigue in soccer players. Additionally, some earlier investigations demonstrated that a performance test such as CMJ height is generally insensitive to acute changes in workload. Performance tests, in short, have the downsides of being time-consuming, having the potential to cause the athletes to become even more fatigued, and providing little insight into their level of fatigue.

Monitoring biochemical, physiological, hormonal and immunological variables such as blood lactate, creatine kinase (CK), testosterone and cortisol or just regular blood and saliva are becoming increasingly popular for fatigue-identifying purposes. In Mclellan et al. (2011) an increase in CK is indicative of tissue damage and is suggested employing it to monitor acute recovery after Rugby League match action. In Beneke et al. (2011) blood lactate concentration is defined as sensitive to changes in exercise intensity and duration. According to Twist et al. (2013), markers such as regular blood and saliva give precise information on a player's health state and are therefore beneficial for tracking fatigue. However, there are still several concerns with these types of variables. Studies have shown a positive correlation between collision frequency and CK, suggesting that CK would not be able to distinguish between muscle soreness caused by mechanical damage and that caused by blunt trauma, this worry was addressed by Twist et al. (2013). The considerable variability of CK and its poor temporal association with muscle recovery are two additional issues Halson (2014) raises with respect to this biomarker. According to Borresen et al. (2008), the blood lactate sensitivity to exertion may be impacted by external variables such as atmospheric conditions, diet, prior exercise, exercise duration, intensity, or dehydration. In summary, the proposed use of biochemical, hormonal, and/or immunological tests as indicators of the internal load is somewhat unjustified considering the area's scarce research. These methods could have a poor temporal association with performance and are costly, invasive, time-consuming, and challenging to execute in practical situations (Tavares et al., 2017).

Even though there is a wide variety of research in this area, no single, reliable diagnostic indicator of fatigue and/or internal load has been established.

On the other hand, following earlier efforts by other authors, Novak et al. (2021) propose an innovative approach in which players' physical activity is measured using a concept known as worst-case scenario (WCS), which integrates a number of contextual aspects, using rolling time periods. The peak 3-min (also 5-min rolling window was analysed) for total distance, high-speed running distance (>5.5 m/s), and sprinting distance (≥7.0 m/s) were used to establish the suggested WCS technique.

This established approach by Novak et al. (2021) had also already been leveraged by the FA Performance Team during the 2020 Football Conference organised by the UK Strength and Conditioning Association, although not following the same exact definition for the WCS. In their pitch presentation, they proposed using peak game values rather than any other indicators to evaluate the most demanding period of a match for diverse metrics. They came to the conclusion that there is a significant difference between the peak that players experience during matches and the peak they replicate during training.

2.4. GPS validity and reliability

The introduction of global positioning systems (GPS) for gathering and analysing movement data has revolutionized the monitoring of external loads and allowed for the evaluation of the most significant physical activities made by players. GPS allows tracking the movement of a player during exercises. The use of this technology to monitor team sports is becoming more and more popular, in accordance to Halson (2014). In discontinuous team sports, GPS-based measurements like total distance (TD), average running speed, and distance covered at higher intensities have been employed to assess physical performance. Research, however, indicates that high speeds reduce the accuracy of GPS-measured distance (Beato et al. 2016; Scott et al. 2013). According to published studies, measures of validity, which explain the discrepancy between the data measured by the unit and a set of criteria measure, and reliability, which refers to the replicability of test results on subsequent occasions, are taken into consideration when validating a GPS unit (Beato et al. 2018). Sample rate, velocity, exercise length and type are just a few examples of the variables that might affect GPS reliability when tracking movement. According to research (Scott et al. 2013; Halson 2014; Beato et al. 2016), GPS reliability decreases with increasing movement velocity. Besides that, multiple studies (Beato et al. 2016, 2018) have demonstrated that a greater sample rate gives a more accurate and reliable representation of the mobility needs of the athlete. Beato et al. (2018) reported that 10 Hz GPS devices have superior accuracy in TD covered and Vpeak compared to 1 and 5 Hz devices. Additionally, Thorpe et al. (2015) highlight an interesting argument that participants should always wear the same GPS device for each session in order to avoid interunit errors.

Due to their accuracy, reliability, and coefficient of variation, STATSports GPS devices are among the most frequently used equipment in elite sports. This device, which was launched in August 2017, can recognize and track several satellite systems to continue providing the most precise positioning data. Beato et al. (2016, 2018) and Thornton et al. (2019) analysed the validity and reliability of the STATSports Apex unit and established its effectiveness for tracking player movement. The investigation conducted by Beato et al. (2016, 2018) revealed that the Apex unit appears to have a small bias (<5%) for distance measurements and Vpeak (20-meter sprint), confirming the Apex model's validity. This unit also demonstrated high levels of accuracy when the authors investigated metrics specific to sports. In conclusion, Apex units could be used to assess football players' sprint performance, Vpeak, and distances covered. According to Thornton et al. (2019), who confirmed the earlier findings, the Apex unit appears to have great inter-unit reliability and a good coefficient of variation (5%) for all distances assessed (5-10m, 10-15m, 15-20m, and 20-30m).

In conclusion, it seems from the literature that STATSports' Apex GPS unit is a reliable and accurate GPS device that can deliver precise positional data.

2.5. Association vs Prediction

McCall et al. (2017)'s study has highlighted a major topic: the differences between prediction and association. The researchers concluded that there is still a profound misunderstanding of the difference between association and predictive power in the world of sports science, mainly due to a lack of a clear definition of these terms. Similarly, to explanatory studies, association studies will allow explaining why a particular event occurs. These investigations are often interested in finding any underlying correlations between variables that might explain one another. If a correlation between one or more variables and an outcome is observed, it might be tempting to assume that these could be employed as forecasting tools. However, statistically substantial correlations do not ensure that a variable may distinguish between variables that are likely to experience a specific event and those that do not. Conversely, prediction enables us to identify outputs and predict outcomes with a certain degree of accuracy, at the micro-scale. It enables at an individual level the application of a conceptual framework and forecast outcomes given known parameters (Ruddy et al., 2019). To put that in perspective, association studies help to clarify why a certain outcome may have occurred, but we cannot confidently say that such association will occur once more. With prediction, researchers may forecast an event given a set of inputs with a particular level of accuracy. We are provided with a list of outcomes reported by both terms in McCall et al. (2017) that may aid in differentiating them. P-values, the correlation coefficient (R^2), the odds ratio (OR), the relative risk (RR) or the incidence rate ratio (IRR) are typically used to report associations. Accuracy, area under the curve (AUC), sensitivity, specificity, positive and negative predictive value (PPV & NPV), likelihood ratio or receiver operating characteristic (ROC) curves are typical words used to describe prediction experiments.

Most sports science research studies that focus on fatigue are reported mostly as association studies than as prediction studies.

2.6. Fatigue Prediction Modeling

There are not too many investigations on fatigue prediction modelling, however, Thorpe et al. (2017) created a framework based on a regression model to assess how sensitive fatigue markers were to daily different training loads accumulated over the past four days over a brief in-season period. A seven-point Likert scale (from 1 to 7, with 1 denoting very, very poor and 7 designating very, very good) was employed in this experiment to evaluate the state of wellness. According to the output regression, fatigue decreased by one unit for every 400 meters of total high-speed running distance. Despite the study's interesting findings, it cannot be used as a prediction model.

Regardless of the fact that there is a gap in the literature about prediction modelling, especially in high-frequency prediction, there are some significant concepts and contributions that we should seriously consider concerning the former.

Halson (2014) highlights that using scientific and statistical methods for detecting substantial changes can provide confidence and assurance to professionals. In a team environment, it's crucial to ensure that everyone is appropriately monitored.

Halson also mentions some essential elements to take into account when implementing a sustainable monitoring system, including (1) user-friendliness, (2) efficiency in result reporting, (3) potential to be used without internet access, (4) easily transposed into simple outcomes, (5) flexibility and adaptability for different sports and athletes, (6) recognition of meaningful changes should be simple and efficient, (7) must be ready to provide both individual and group responses, (8) cognitive flexibility.

Chapter 3.

RESEARCH METHODOLOGY

3.1. Methodology

The approach adopted to process data is quite similar to CRISP-DM (Cross Industry Standard Process for Data Mining), after a literature review that is analogous to Business Understanding, follows Data Understanding infused on **3.2 Data Collection** and **3.3 Raw Data**, Data Preparation, and Modelling. Evaluation in chapter **5**, and finally a **Deployment Suggestion** in chapter **6.**

3.2. Data Collection

A Portuguese elite-level club facilitated access to GPS-tracked training and match sessions recorded using STATSPORTS' Apex GPS unit that works at 10Hz, which translates to 10 records per second. The GPS device was worn by the players and was housed in a tiny pocket, of an undershirt, that was posterior to the scapulae. This club provided data corresponding to 6484 monitored (individual) sessions, training and match distributed in 6484 different .csv files, i.e., one file contains data from one player for one session. The data was provided in its raw state and was taken directly from the GPS device provider's database. Due to the large number of files and their dispersal, was required to firstly group all data in one place so eventual transformations would be easily applied to all data in the same way. These files all shared the same structure in their raw state, data was organized into the following fields: Player Display Name, Time, Latitude, Longitude, Speed (m/s), Heart Rate (bpm), and Instantaneous Acceleration Impulse. Latitude and Longitude were displayed in a coordinate format in decimal degrees. There were inconsistencies in the heart rate measurements; while some players had theirs recorded, others did not. Furthermore, it was difficult to comprehend genuine accelerations and decelerations due to Instantaneous Acceleration Impulse's inconsistency in not differentiating between acceleration and deceleration motions. To work for this investigation, around 350 million rows of data were provided.

After having access to all facilitated .csv files an ETL (Extract, Transform and Load) process (Figure 3.1) was carried out. In the beginning, all.csv files were grouped in a MySQL Database according to the raw data structure to make all data more accessible and to speed up upcoming transformation processes. Data from the files were extracted using the SPSS Modeler software and inserted in the newly constructed database.

Following consolidating all of the information into a single repository, SPSS Modeler software was again utilized to explore and prepare the data by doing all necessary transformations and storing it in a new MySQL database.

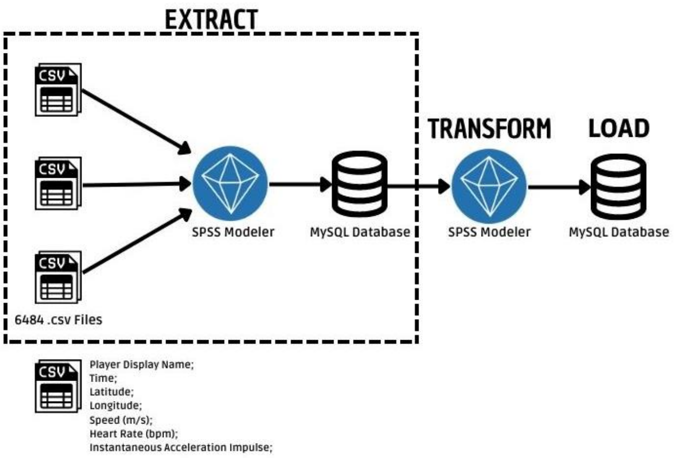

FIGURE 3. 1: ETL process employed

3.3. Raw Data

Of the 6484 monitored sessions, 88% were related to training (5695) and the remainder were match sessions (789). Data were collected from 208 distinct participants, representing both genders, on 138 different dates between 19/07/2021 and 28/02/2022, with men (182) being the most represented with 87.5% of the total (Figure 3.2).

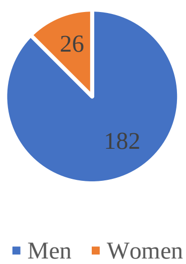

FIGURE 3. 2: Raw Data Gender Distribution

The age of players under observation ranged from 12 to 34. The overall average age was given at 16.8. Women (22.3) that were monitored were on average older than men (16) (Figure 3.3).

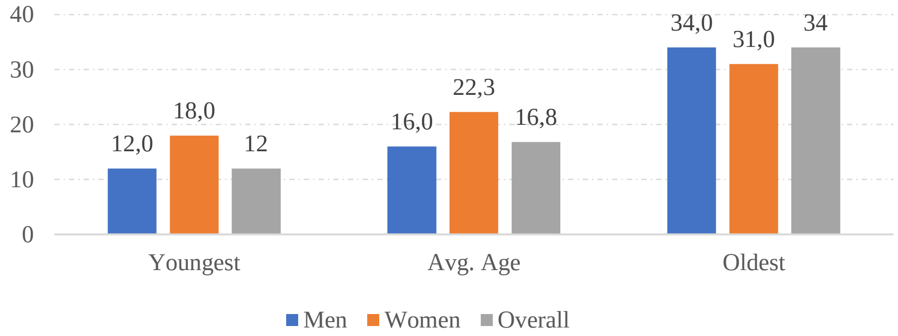

FIGURE 3. 3: Raw Data Age analysis by gender and overall

For all players were assigned their correspondent, most frequent, playing position. Positions assigned were categorized into 6 different positions: Goalkeeper (GK), Fullback (FB), Centre-Back (CB), Midfielder (MID), Winger (W) and Striker (ST). Position frequencies derived from raw data are represented in Figure 3.4.

FIGURE 3. 4: Raw Data Number of Players by position

Figure 3.5 displays the average speed (m/s) for the various positions. This technique allows for a preliminary evaluation of the variations between training and match sessions. However, no data preparation or cleaning processes have yet been implemented, therefore this analysis is just being used for demonstration purposes, there are hardly any significant takeaways from this.

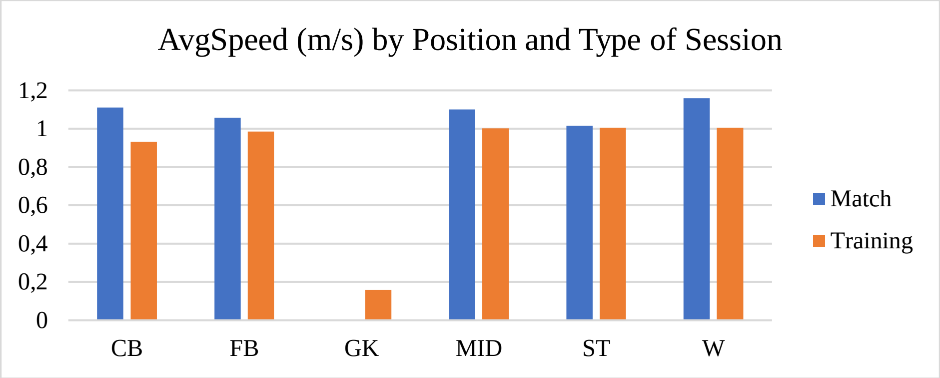

FIGURE 3. 5: Raw Data Average Speed analysis by Position and Type of Session

With the exception of wingers and goalkeepers, as only men are represented in this position, female players displayed greater average speed ratings than male players for practically every position. However, this could be explained by the fact that the women in this sample are, on average, older than the men.

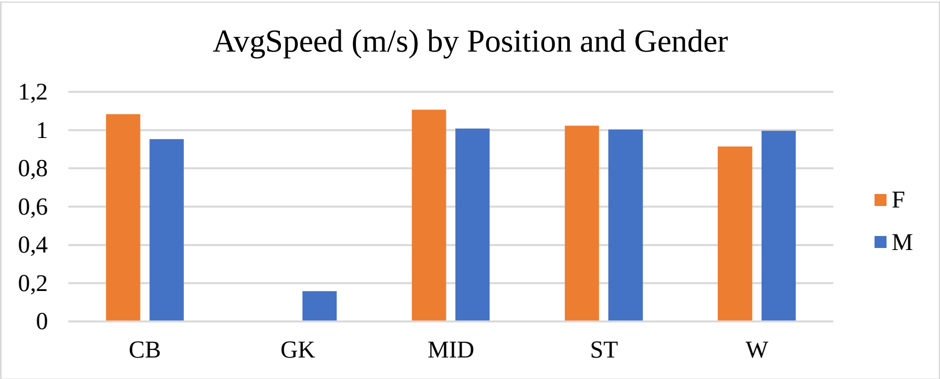

FIGURE 3. 6: Raw Data Average Speed analysis by Position and Gender

3.4. Data Preparation

Data preparation procedures were carried out using IBM SPSS Modeler 18.2 software.

Certain thresholds were established to exclude redundant data in order to have a consistent, coherent, and trustworthy dataset. Players with more than 10 documented training or game sessions and players with both recorded training and match sessions were those who qualified. Players who didn't meet these requirements were discarded. Implementing this initial step allowed to reduce the number of players to 175 and the total recorded sessions to 6045, 5321 for training and 724 for matches (Figure 3.7). In addition, compared to the preceding sample, the final dataset was reduced by one date of monitored sessions. The percentage of each gender among the players remained constant, with 154 men and 21 women overall (Figure 3.8). Regarding age statistics, the minimum age stayed the same, the maximum age decreased to 31 years old, and the mean age, which considers both genders, also decreased to 16.72 ± (2.9) and CV=17.51%.

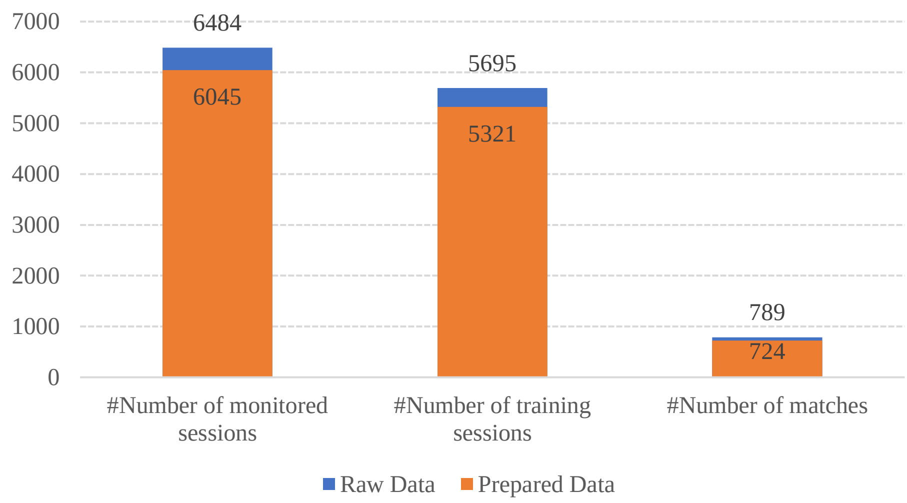

FIGURE 3. 7: Raw Data vs Prepared Data Number of Sessions

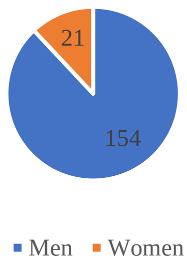

FIGURE 3. 8: Prepared Data Gender Distribution

The exclusion of players who didn't fit the qualifications (Figure 3.9) had the most detrimental impact on midfielders and forwards, although goalkeepers also lost representation as a result of not being eligible.

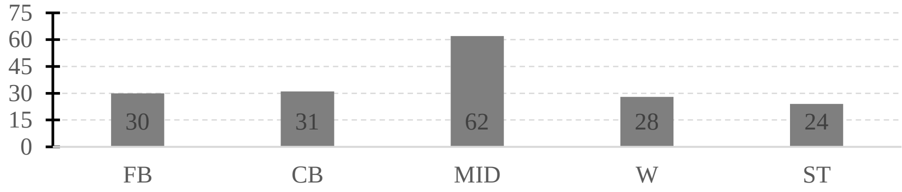

FIGURE 3. 9: Prepared Data Number of Players by position

Following the exclusion of cases that did not relate to the defined thresholds, the idea of a new aggregate level was explored. It is not practicable to operate with such a high degree of granularity since raw data granularity was collected in deciseconds, this translates to 600 records every minute and 350 million records over all the 6484.csv files, and as demonstrated in earlier works, authors often utilize 3 (Novak et al., 2021), 5 (Mohr et al., 2003; Mohr et al., 2005; Lamberts et al., 2010), or even 15-minute (Mohr et al., 2003; Mohr et al., 2005; Reilly et al., 2008; Krustrup et al., 2010) intervals. For the purposes of this work, the level of data aggregation will be 1 minute in order to provide the staff with a high-frequency prediction solution that can run in close to real-time. A larger time period for data aggregation might result in significant insights being lost. Some additional variables were derived from original fields throughout the process of reducing the granularity level of the data in order to preserve crucial information. The distance travelled was one of them and was calculated using the haversine formula:

$$\begin{aligned} Distance\ (m) = \ & [\arccos\big(\sin(\text{Lat } 1)\ .\ \sin(\text{Lat } 0) + \ \cos(\text{Lat } 1)\ .\ \cos(\text{Lat } 0) \\ & * \ \cos(\text{Lon } 1\ -\ \text{Lon } 0)\big)\ .\ 6372.8\ .\ 1000] \end{aligned} \tag{3. 1}$$

This required the conversion of latitude and longitude data to radians. Also, because of inconsistencies with the Instantaneous Acceleration Impulse field, Acceleration was recalculated, and Deceleration was calculated before aggregation, both derived from Speed. Only variations of 1 were taken into account as acceleration for speed increases and deceleration for speed reductions in order to assure the significance of both variables. Additionally, based on speed, it was possible to compute the frequency of speeds greater than 5.5 (high-speed running) and 7 m/s (sprint), following previous works such as Novak et al. (2021), as well as the distance covered at each speed threshold. Data was subsequently summarized at the minute level after creating new variables based on Speed at the highest level of granularity. The average value for that minute was computed for Latitude, Longitude, Speed, Acceleration, and Deceleration. Additionally, the maximum and minimum values for speed, acceleration, and deceleration were computed, and the last two were still calculated at their frequency throughout the minute.

Outlier identification and management were done after data had been aggregated down to the minute level.

Based on the work developed by Novak et al. (2021), variables Distance, Dist_HSR and Dist_SP were targeted for a Principal Components Analysis (PCA) using a Varimax rotation. This method allowed for the reduction of these three variables' dimensionality for only one component. The PCA follows a formula like: β0 X0 + β1 X1 + β2 X2 + … βi Xi.

As a result, in this case, the formula to calculate the component extracted from the PCA procedure is:

$$CI = 0.01061 \,.\, Distance + 0.07335 \,.\, Dist_{HSR} + 0.1247 * Dist_{SP} - 0.8674 \tag{3. 2}$$

Then a new variable, Intensity_Index, is computed as the calculation of the percentage fractional rank of CI.

$$Intensity_{Index} = Rank\ \%\ (CI) \tag{3. 3}$$

Therefore, Intensity_Index follows a scale from 0-100 and is used to assess the intensity throughout the course of a 1min period, as previously explained. 0 indicates less intensity, while 100 indicates higher intensity.

From Intensity_Index a new variable, Fatigue, was derived, based on a condition:

$$\begin{cases} Fatigue_t = 1 \rightarrow Intensity\_Index_t \geq \alpha \\ Fatigue_t = 0 \rightarrow Intensity\_Index_t < \alpha \end{cases} \tag{3. 4}$$

For the purposes of developing the algorithm and the framework as a whole, α was considered as 70, that is, an Intensity_Index above 70 may have cumulative effects for the players. This approach may be used for any alpha, based on the circumstances that the technical team judges to be levels of intensity that may turn out to be persistent. After calculating Fatigue, a cumulative fatigue variable was computed, CFatigue.

Now, Intensity_Level was calculated based on CFatigue. It is the result of a percentage fractional rank of CFatigue.

$$Intensity_{Level} = Rank \, \% \, (CFatigue) \tag{3. 5}$$

Intensity_Level represents the evolution of a player's intensity over the course of the session while accounting for the prior Intensity_Index. Additionally, it is described on a scale from 0 to 100, with 100 denoting the highest intensity level ever recorded and 0 denoting a lowered intensity level.

The practical application of both variables, Intensity_Index and Intensity_Level, is shown in figure 3.8. It’s in line with the literature, where authors note that players get more fatigued towards the end of the match, intensity is higher in the first half and longer periods of high intensity require longer periods of recovery. Figure 3.10 demonstrates Intensity_Index's method of measuring the intensity employed throughout 1-minute intervals; the higher the Index, the higher the intensity for that minute. Intensity Level, a continuous variable that measures the level of a match's intensity, is somewhat dependent on the Intensity Index values.

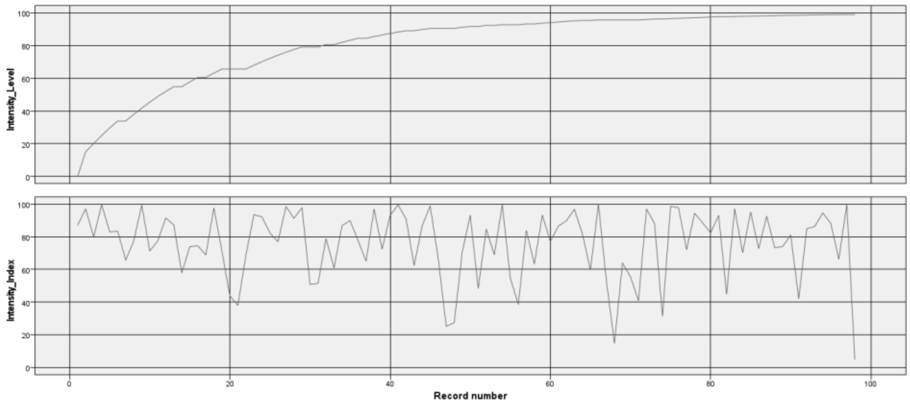

FIGURE 3. 10: Fatigue assessment example

Table 3.1 comprises a Data Dictionary, which illustrates all fields and pertinent calculation procedures used to obtain such attributes, for a better understanding of the work produced in data preparation.

TABLE 3. 1: Prepared Data Dictionary

Attribute	Description	Calculation Procedure
Player	Player identifier	
Date	Session Date	
Hour	Record time (Hour)	
Minute	Record time (Minute)	
Avg_Lat	Average Latitude coordinate recorded during a minute	
Avg_Lon	Average Longitude coordinate recorded during a minute	
Avg_Speed	Average speed (m/s) recorded during a minute	
Min_Speed	Minimum speed (m/s) recorded during a minute	
Max_Speed	Maximum speed (m/s) recorded during a minute	
Avg_Acceleration	Average acceleration (m/s) recorded during a minute	Acceleration is calculated based on speed discrepancies measured in seconds. If Speed increases by more than 1 m/s from one record to another, it is considered an acceleration motion.
Min_Acceleration	Minimum acceleration (m/s) recorded during a minute	
Max_Acceleration	Maximum acceleration (m/s) recorded during a minute	
Num_Acceleration	Number of acceleration movements recorded during a minute	
Avg_Deceleration	Average deceleration (m/s) recorded during a minute	Deceleration is calculated based on speed discrepancies measured in seconds. If Speed decreases by more than 1 m/s from one record to another, it is considered a deceleration motion.
Min_Deceleration	Minimum deceleration (m/s) recorded during a minute	
Max_Deceleration	Maximum deceleration (m/s) recorded during a minute	
Num_Deceleration	Number of deceleration movements recorded during a minute	
Distance	Distance covered in a minute	Calculated based on GPS coordinates, every second.
Accumulated_Dist	Accumulated distance during the session	Calculated as the sum of Distance during the session.
Num_HSR	Number of times a player exceeded 5.5 m/s speed, during a minute	
Dist_HSR	Distance covered at a >5.5 m/s speed, during a minute	
Num_SP	Number of times a player exceeded 7 m/s speed, during a minute	
Dist_SP	Distance covered at a >7 m/s speed, during a minute	
Type	Session identifier	

Records_Minute	Number of records per minute	
Position	Player position	
Detailed_Position	Detailed player position	
CodPos	Player position identification code	
Gender	Player gender	
BirthDate	Player’s date of birth	
Age	Calculated based on a session date and birth date	
Intensity_Index	Evaluate player’s intensity during a 1min period	
Intensity_Level	Evaluate the player’s intensity during a session	

3.5. Descriptive Statistics

Table 3.2 presents the most relevant descriptive statistics from all data fields included in the final dataset. Given that a large number of records were equal to 0, the majority of the Coefficient of Variation (CV) values are larger than what was perhaps anticipated, with a particular focus on the frequency and distance covered by HSR and SP. According to data, mean Avg_Speed was set at 0.998 m/sec, much below the HSR and SP standards. Soccer is a sport that has significant intermittent speed peaks, which helps to explain this.

During a one-minute period, acceleration and deceleration frequency and impact are very similar, although deceleration might be imprecisely determined as it is a result of a decrease of speed higher than 1m/s.

Based on an analysis of the factors used to determine the intensity variables, players typically travel 62.438 meters in a minute, with 3.3% of the distance being completed by high-speed running (>5.5 m/sec) and 0.7% by sprinting (>7 m/sec).

TABLE 3. 2: Dataset's fields' most pertinent descriptive statistics

	N		Mean	Std. Deviation	Coefficient of Variation	Min.	Max.	Percentiles						
	Valid	Missing						1	5	25	50	75	95	99
Age	546209	0	16.7	2.9	0.2	12	31	13	13	15	16	18	22	8
Avg_Speed (m/sec)	546209	0	1.0	0.7	0.7	0.0	5.9	0.0	0.0	0.4	0.9	1.5	2.2	2.7
Min_Speed (m/sec)	546209	0	0.1	0.2	2.6	0.0	5.3	0.0	0.0	0.0	0.0	0.0	0.6	1.0
Max_Speed (m/sec)	546209	0	3.2	2.0	0.6	0.0	9.7	0.0	0.1	1.3	3.3	4.7	6.5	7.6
Avg_Acceleration (m/sec)	546209	0	1.4	0.7	0.5	0.0	10.0	0.0	0.0	1.2	1.6	1.8	2.2	2.6
Max_Acceleration (m/sec)	546209	0	2.3	1.4	0.6	0.0	11.7	0.0	0.0	1.4	2.6	3.3	4.3	5.0
Min_Acceleration (m/sec)	546209	0	0.9	0.4	0.5	0.0	10.0	0.0	0.0	1.0	1.0	1.1	1.3	1.7
Num_Acceleration	546209	0	11.8	10.5	0.9	0	60	0	0	2	10	19	32	40
Avg_Deceleration (m/sec)	546209	0	1.3	0.6	0.5	0.0	14.2	0.0	0.0	1.2	1.5	1.7	2.0	2.2
Max_Deceleration (m/sec)	546209	0	2.2	1.3	0.6	0.0	28.2	0.0	0.0	1.3	2.4	3.0	4.0	5.0
Min_Deceleration (m/sec)	546209	0	0.9	0.4	0.5	0.0	10.0	0.0	0.0	1.0	1.0	1.1	1.3	1.7
Num_Deceleration	546209	0	12.2	10.9	0.9	0	60	0	0	2	10	19	33	42
Distance (m)	546209	0	62.4	42.3	0.7	0.0	297.2	2.6	6.5	25.1	58.4	93.8	135.7	164.4
Accumulated_Dist (m)	546209	0	3059.6	2370.1	0.8	0.0	17338.8	33.8	242.9	1239.7	2620.3	4317.4	7449.1	11279.4
Num_HSR	546209	0	0.3	1.1	3.4	0	25	0	0	0	0	0	2	5
Dist_HSR (m)	546209	0	2.0	7.0	3.4	0.0	154.9	0.0	0.0	0.0	0.0	0.0	13.3	31.4
Num_SP	546209	0	0.1	0.4	7.3	0	15	0	0	0	0	0	0	2
Dist_SP (m)	546209	0	0.4	3.3	7.5	0.0	120.0	0.0	0.0	0.0	0.0	0.0	0.0	15.0
Intensity_Index	546209	0	50.0	28.9	0.6	0.0	100.0	0.9	4.9	24.9	50.0	75.0	95.0	99.0
Intensity_Level	546209	0	49.4	29.2	0.6	0.0	100.0	0.0	3.7	25.0	48.8	74.1	94.8	99.0

At the one-minute period granularity level of analysis (Table 3.3), midfielders had greater levels of mean distance covered and centre-backs the lowest, which is consistent with the literature, given a 95% confidence level. Midfielders, however, revealed the second-lowest values at higher intensities, just below centre-backs. Fullbacks and wingers are the ones that run the most at high-intensity running. For sprinting distance, fullbacks and wingers reported higher values.

TABLE 3. 3: Distance covered by position at different thresholds by the minute

	Record (n)	Distance (m) Mean (SD) – CV %	Dist_HSR (m) Mean (SD) – CV%	Dist_SP (m) Mean (SD) – CV%
Centre-Back	95430	60.6 ± (39.4) – 65.0%	1.6 ± (6.2) – 395.7%	0.3 ± (2.7) – 857.7%
Fullback	95512	61.8 ± (41.5) – 67.1%	2.4 ± (7.4) – 308.5%	0.6 ± (3.9) – 631.2%
Midfielder	189800	63.6 ± (43.8) – 68.9%	1.8 ± (6.8) – 373.4%	0.3 ± (2.9) – 883.1%
Winger	93284	62.8 ± (42.5) – 67.6%	2.5 ± (7.4) – 297.2%	0.6 ± (3.7) – 625.9%
Striker	72183	62.5 ± (42.3) – 67.6%	2.2 ± (7.0) – 321.4%	0.5 ± (3.3) – 729.4%

In general, the distances travelled by positions appear to be equivalent when analysing all of the sessions (Table 3.4), matches and training, taking into consideration that the majority of the records reflect training sessions. Coaches' demands for equal levels of intensity from every player may help to explain this.

Given a 95% confidence level, midfielders reported covering more distance than fullbacks. However, there was no evidence of a statistically significant difference between the groups for the other positions.

With a 95% confidence level, centre-backs reported less Dist HSR covered, followed by midfielders, while wingers observed the most Dist HSR. Considering a 95% confidence level, no evidence of a statistically significant difference between fullbacks and wingers in HSR movement frequency was detected. Considering that the Intensity_Index scale is defined from 0-100, the values addressed do not represent a high level of intensity, which confirms the previous doctrine that soccer is characterized as an intermittent sport. When assessing the Intensity Index, center-backs recorded the lowest values of all the positions, whereas, in the other positions, no statistically significant difference was discovered given a 95% confidence range.

TABLE 3. 4: Intensity_Index and distance covered in an entire session by position at various thresholds

	Record (n)	Distance (m) Mean (SD) – CV%	Dist_HSR (m) Mean (SD) – CV%	Num_HSR Mean (SD) – CV%	Dist_SP Mean (SD) – CV%	Num_SP Mean (SD) – CV%	Intensity_Index Mean (SD) – CV%
Centre-Back	1038	5574.4 ± (2356.4) – 42.3%	240.5 ± (159.2) – 66.2%	23.4 ± (22.8) – 97.0%	29.4 ± (48.9) – 166.3%	4.0 ± (6.6) – 164.6%	48.7 ± (10.6) – 21.8%
Fullback	1085	5437.7 ± (2069.2) – 38.1%	348.9 ± (232.6) – 66.7%	34.5 ± (27.1) – 78.3%	54.0 ± (68.8) - 127.4%	7.3 ± (9.2) – 126.0%	50.5 ± (10.1) – 20.0%
Midfielder	2083	5794.5 ± (2257.2) – 39.0%	285.1 ± (212.4) – 74.5%	27.3 ± (25.7) – 94.4%	30.1 ± (50.5) - 167.6%	4.1 ± (6.8) - 165.8%	50.1 ± (10.4) – 20.8%
Winger	1032	5666.9 ± (2363.5) – 41.7%	389.2 ± (222.7) – 57.2%	36.6 ± (29.0) – 79.4%	53.6 ± (67.8) - 126.4%	7.3 ± (9.1) – 125.0%	50.7 ± (10.8) – 21.3%
Striker	805	5590.1 ± (1996.1) – 35.7%	352.9 ± (213.7) – 60.6%	32.2 ± (27.5) – 85.7%	40.7 ± (59.6) - 146.4%	5.6 ± (8.0) – 144.5%	50.5 ± (9.5) – 18.8%

Filtering for match sessions only (Table 3.5), every position's distance covered rises. Fullbacks recorded the lowest distance covered during matches along with strikers without being able to detect a statistical difference between the groups for a 95% confidence interval. Also, no statistical significant evidence was found between centre-backs, midfielders and wingers. The prior notion for Dist_HSR considering training and match sessions remains true in this circumstance. Wingers reported the highest level of intensity in their matches, according to the Intensity_Index metric.

TABLE 3. 5: Intensity_Index and distance covered during a match by position at various thresholds

	Record (n)	Distance (m) Mean (SD) - CV%	Dist_HSR (m) Mean (SD) - CV%	Num_HSR Mean (SD) - CV%	Dist_SP (m) Mean (SD) - CV%	Num_SP Mean (SD) - CV%	Intensity_Index Mean (SD) - CV%
Centre-Back	143	8498.7 ± (3721.7) - 43.8%	240.5 ± (159.2) - 66.2%	39.7 ± (26.2) - 65.9%	44.8 ± (55.6) - 124%	6.1 ± (7.4) - 122.8%	55.9 ± (15.0) - 28.9%
Fullback	107	7454.1 ± (3793.2) - 50.9%	348.9 ± (232.6) - 66.7%	57.3 ± (37.9) - 66.1%	100.2 ± (102.3) - 102.1%	13.5 ± (13.6) - 100.6%	54.4 ± (17.9) - 32.9%
Midfielder	250	8222.9 ± (3599.8) - 43.8%	285.1 ± (212.4) - 74.5%	46.9 ± (35.0) - 74.5%	45.7 ± (121.7) - 121.7%	6.3 ± (7.5) - 120.2%	55.0 ± (15.9) - 28.9%
Winger	132	8447 ± (4078.3) - 48.3%	389.2 ± (222.7) - 57.2%	64.6 ± (35.8) - 55.4%	99.0 ± (96.5) - 86.5%	13.5 ± (11.5) - 85.1%	58.3 ± (15.3) - 26.2%
Striker	90	7787.1 ± (3230.0) - 41.5%	352.9 ± (213.7) - 60.6%	57.8 ± (38.0) - 65.8%	80.2 ± (105.9) - 105.9%	10.9 ± (11.4) - 104.9%	54.5 ± (14.6) - 26.9%

Considering a 95% confidence interval, no indication of a statistical difference between the halves could be found for distance covered. The second half of the game, however, produced greater values recorded by Dist_HSR and Dist_SP than the first. However, despite the fact that the mean is higher in the first half, the 95% confidence intervals for the mean intersect, denying the presence of a statistically significant difference between halves given the standard deviations seen from the Intensity_Index.

TABLE 3. 6: Intensity_Index and distance covered during each match half

	Record (n)	Distance (m) Mean (SD) - CV%	Dist_HSR (m) Mean (SD) - CV%	Dist_SP (m) Mean (SD) - CV%	Intensity_IndexMean (SD) - CV%
1st Half	724	4115.8 ± (2325.9) - 56.5%	144.7 ± (130.6) - 90.2%	29.3 ± (41.9) - 143.0%	54.8 ± (32.4) - 59.2%
2nd Half	724	4029.6 ± (1992.8) - 49.5%	168.2 ± (149.8) - 89.0%	38.2 ± (52.5) - 137.4%	52.1 ± (33.4) - 64.1%

Even though the mean is higher in the first half, when differences between halves based on playing positions are compared (Table 3.6), the 95% confidence intervals for the mean intersect, ruling out the existence of a statistically significant difference given the standard deviations observed for Intensity Index.

TABLE 3. 7: Intensity_Index and distance covered during each match half by position

	Half	Record (n)	Distance (m) Mean (SD) - CV%	Dist_HSR (m) Mean (SD) - CV%	Dist_SP (m) Mean (SD) - CV%	Intensity_Index Mean (SD) - CV%
Centre-Back	1	143	4250.4 ± (2100.4) - 49.4%	112.6 ± (85.8) - 74.2%	20.1 ± (29.1) - 144.8%	55.7 ± (29.8) - 53.6%
Centre-Back	2	143	4207.9 ± (2054.1) - 48.8%	127.6 ± (121.0) - 94.1%	24.6 ± (37.9) - 154.1%	53.4 ± (30.7) - 57.6%
Fullback	1	108	3771.9 ± (2268.1) - 60.1%	159.4 ± (131.9) - 82.7%	45.7 ± (57.8) - 126.4%	53.4 ± (33.3) - 62.3%
Fullback	2	108	3714.1 ± (1975.9) - 53.2%	190.7 ± (153.7) - 80.6%	54.2 ± (62.1) - 114.6%	50.8 ± (34.1) - 67.2%
Midfielder	1	251	4129.7 ± (2369.4) - 57.4%	128.6 ± (129.2) - 100.5%	18.3 ± (28.4) - 155.6%	53.7 ± (33.0) - 61.5%
Midfielder	2	251	4081.3 ± (1976.1) - 48.4%	155.9 ± (151.3) - 97.1%	27.2 ± (44.5) - 163.9%	51.7 ± (34) - 65.7%
Winger	1	132	4381.4 ± (2489.1) - 56.8%	191.3 ± (144.7) - 75.6%	46.0 ± (48.4) - 105.2%	58.3 ± (32.4) - 55.5%
Winger	2	132	4112.3 ± (2080.6) - 50.6%	197.2 ± (149.0) - 75.6%	53.0 ± (57.2) - 107.9%	53.2 ± (34.0) - 63.9%
Striker	1	90	3886.4 ± (2345.8) - 60.4%	154.8 ± (148.8) - 96.1%	30.5 ± (44.1) - 144.7%	52.5 ± (33.3) - 63.5%
Striker	2	90	3859.2 ± (1809.4) - 46.9%	197.8 ± (167.4) - 84.6%	49.7 ± (60.5) - 121.7%	50.9 ± (34.2) - 67.2%

Given the mean values, it might have been more physically demanding for players to cover longer distances more steadily and slowly in the first half, but just like with Intensity Index, the 95% confidence intervals for the mean intersect, making it difficult to confirm any statistically significant differences.

Taking these aspects into consideration, of the different variables presented in this work, it's important to understand the disparities between training and matches. Are athletes training at lower, equal or higher intensities compared to what they'd experience during matches? It is important to point out that throughout the week, coaches only attempt to raise the intensity level in specific training sessions to that experienced during games, giving also importance to the presence of training sessions with more technical and tactical components. Keeping in mind that this work covers all forms of training and does not distinguish between tactical, technical, or physical training.

Since training sessions generally last longer than matches, a variable called Index was developed to normalize each session's duration on a scale of 0-100 so that matches and training sessions could be compared.

Opening with the average and average maximal speed (Figures 3.11 and 3.12) for each session type, it is notorious that players run at a higher speed during matches than during training, even though the maximal speed declines more quickly during matches while it remains more constant throughout training.

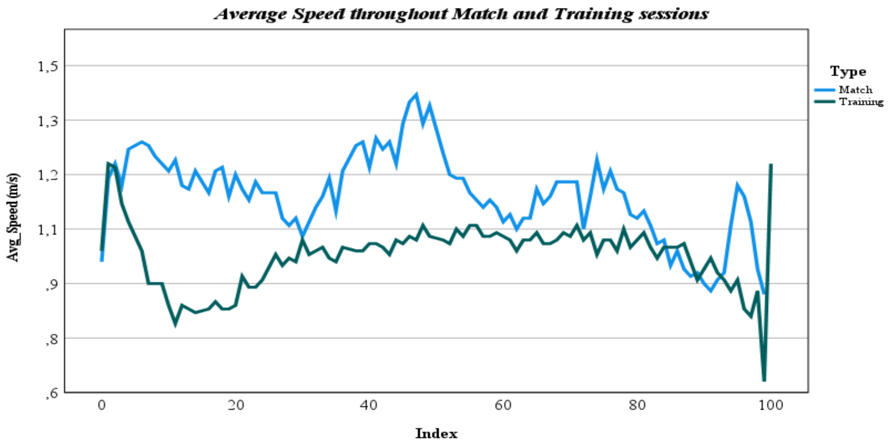

FIGURE 3. 11: Average Speed comparison between matches and training

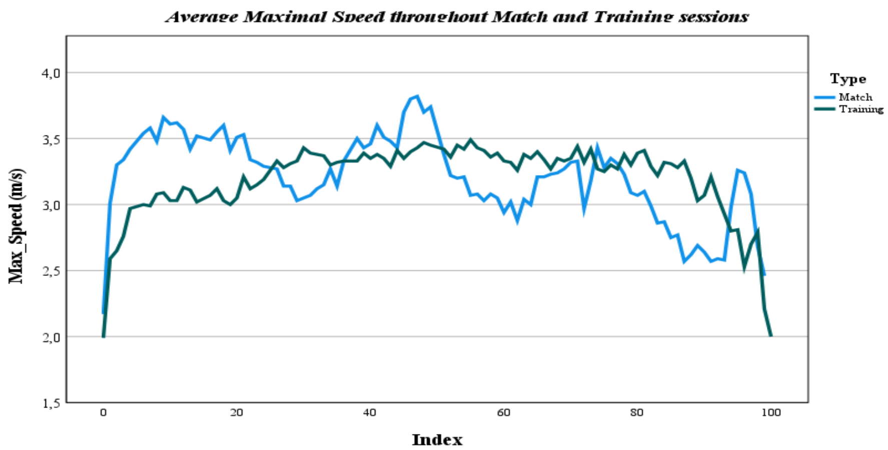

FIGURE 3. 12: Average Maximal Speed comparison between matches and training

Looking at the three crucial elements (Figures 3.13, 3.14 and 3.15) that constitute our Intensity_Index variable, but considering them cumulatively, it becomes clear that players cover more ground at any applied threshold during matches than in training. The biggest disparities are faced when running at higher speeds, particularly high-speed running. Increasing the amount of high-speed running during training may make players more fatigued, but it may also help them avoid injuries.

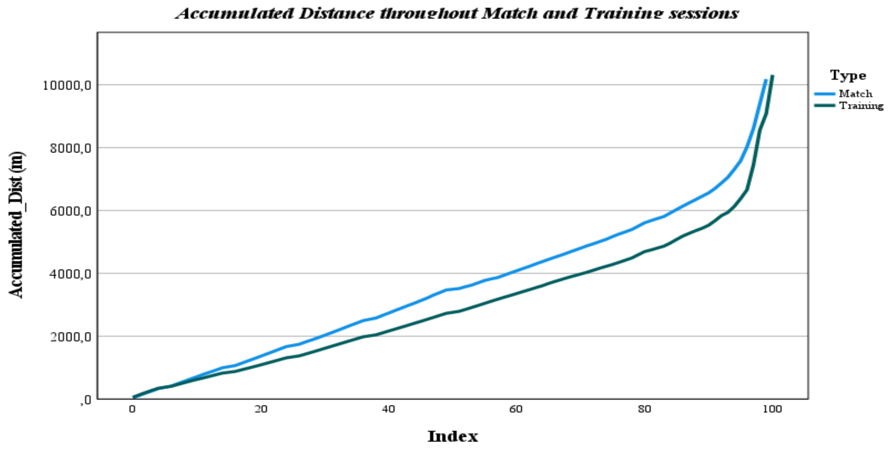

FIGURE 3. 13: Accumulated Distance covered comparison between matches and training

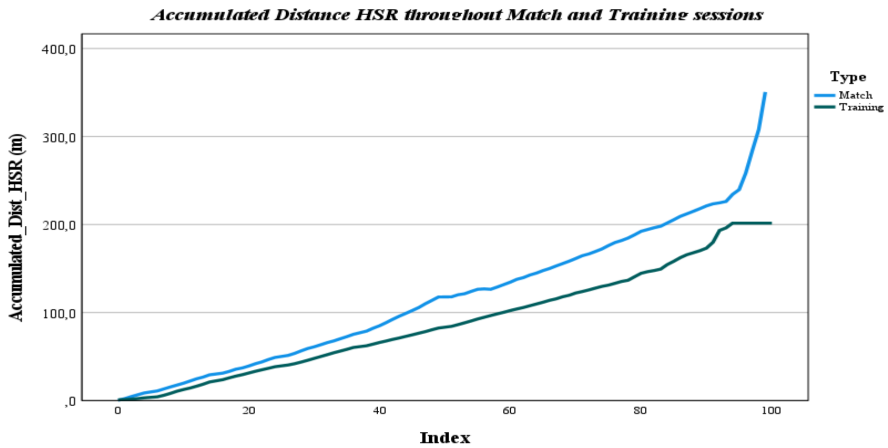

FIGURE 3. 14: Accumulated Distance covered at HSR comparison between matches and training

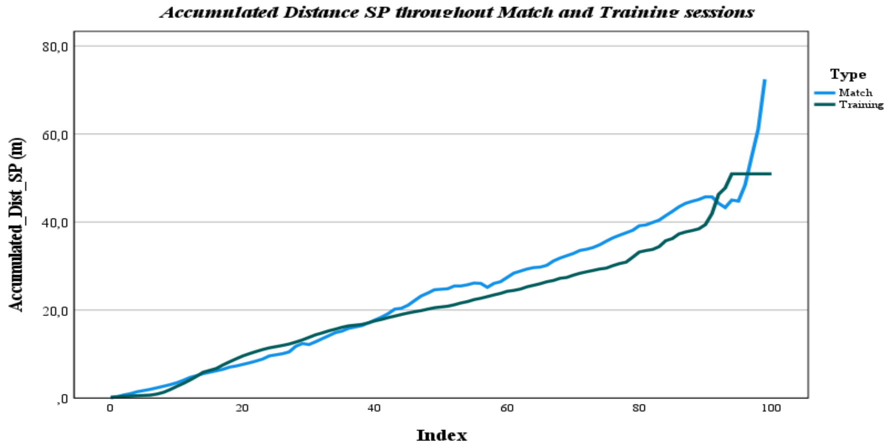

FIGURE 3. 15: Accumulated Distance covered at SP comparison between matches and training

Given the previous analysis, it is probably unnecessary to analyse the data below to realize that players have lower intensity demands while training than they do during matches. However, if there were any questions, Figures 3.16 and 3.17 clear them out. Players are subjected to higher intensity demands (Intensity_Index) during matches than they are during training, which could also cause a higher degree of cumulative intensity (Intensity_Level) at the end of the game than at the closing of the practice.

FIGURE 3. 16: Average Intensity_Index comparison between matches and training

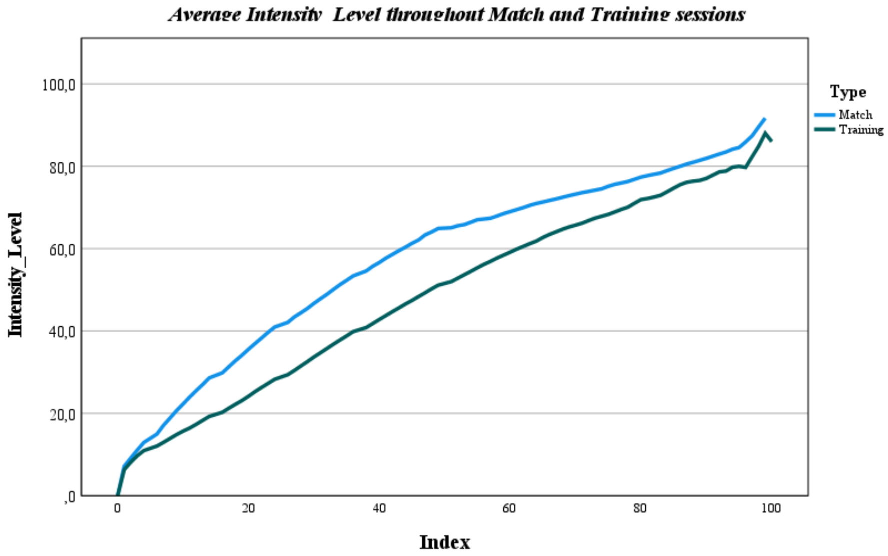

FIGURE 3. 17: Average Intensity_Level comparison between matches and training

This analysis supports the perspective put out by the FA Performance Team at the UKSCA 2020 Football Conference. In practice sessions, players do not replicate the most demanding peaks that they do in matches.

Chapter 4.

MODELLING

To accomplish the aforementioned research objectives, which include creating a high-frequency model based on near real-time updates to data from players' GPS localization and their physical performance throughout the match, a classification problem is more adequate. This will enable the model to distinguish between Fatigue/Not Fatigue classes. However, instead of using a binary classification approach, the model's dependent variable was established with three distinct classes based on Intensity Level. The three classes generated follow a colour palette: Green, Yellow and Red as the objective is to enable the model to work in a similar way to a traffic light: Green, which indicates Not Fatigue and represents Intensity_Level from [0-76[, Yellow, which acts as a pre-sign of fatigue and represents Intensity_Level from [75-92[and Red, which reflects Fatigue and includes Intensity_Level from [92-100]. For the development of the algorithm and the framework as a whole, these thresholds were assigned to all three classes. Depending on the conditions that the technical team determines to be the appropriate degrees of intensity, this method may be used to any other variables.

A third class enables not only the distinction between Fatigue/Not fatigue but also the pre-warning of fatigue to the staff, enabling them to prepare for the management of fatigued players. Following the cutting values established for each class, the result describes an ABC analysis, with Green representing 50% of the cases, Red 30%, and Yellow the reminiscent 20%.

This model's objective is to predict fatigue and support managers to make decisions, using updated data in close to real-time (minute to minute), on if a player needs to be changed in order to improve team performance and become closer to winning (more) matches. Three models were created with this in mind, each for a different prediction timeframe, 5-min, 10-min and 20-min.

The creation of these models to predict fatigue took into account different variables from different environments. Models consider, near real-time match variables but also training sessions.

As was stated previously in the chapter on the literature review, fatigue has a cumulative impact (Tavares et al., 2017), therefore, it was intended for this effect to be included in the models. In order to accomplish this, data from previous training sessions were introduced to the models.

TABLE 4. 1: Training variables

Attribute	Description
Avg_Max_Intensity_Index_Train	The average maximum Intensity_Index reported during training sessions from the 5 days preceding the match.
Avg_Intensity_Index_Train	The average Intensity_Index reported during training sessions from the 5 days preceding the match.
Avg_StdDev_Intensity_Index_Train	The average standard deviation Intensity_Index reported during training sessions from the 5 days preceding the match.
Avg_Max_Intensity_Level_Train	The average maximum Intensity_Level reported during training sessions from the 5 days preceding the match.
Max_Intensity_Level_Train	The maximum Intensity_Level reported during training sessions from the 5 days preceding the match.

Regarding training variables (Table 4.1), training sessions that were recorded over the five days before the match are taken into account and rated based on the intensity through diverse variables.

TABLE 4. 2: New derived variables

Attribute	Description
ΔAvgSpeed	First-order differential from average speed, during the match.
ΔMaxSpeed	First-order differential from max speed, during the match.
ΔAvgAcceleration	First-order differential from average acceleration, during the match.
ΔMaxAcceleration	First-order differential from max acceleration, during the match.
ΔAvgDeceleration	First-order differential from average deceleration, during the match.
ΔMax_Deceleration	First-order differential from max deceleration, during the match.
ΔAvg_Intensity_Index	First-order differential from average Intensity_Index, during the match.
ΔMax_Intensity_Index	First-order differential from max Intensity_Index, during the match.

A few more new cumulative variables (Table 4.2) were constructed to complement the training variables, however, in order to eliminate significant stationary properties, their first-order differential was calculated.

Additionally, socio-demographic indicators like Age, Gender, and CodPos were introduced (code for the player playing position).

Having all variables defined to act as input for the models, in an attempt to model nonlinear relationships, their square was calculated.

The formula used to build the model was as follows:

$$\gamma = f(\beta_i, \mathbf{xi}, \mathbf{xi}^2, \boldsymbol{\Delta\gamma}, \boldsymbol{\gamma^2}) \tag{4. 1}$$

All of the variables used as input to deploy the model using the preceding formula are summed up in Table 4.3.

TABLE 4. 3: Model's input variables

Attribute Variable	Attribute	Attribute Variable	Attribute	Attribute Variable	Attribute
$\beta 1$	CodPos	$x6$	Num_Acceleration	$x14$	ΔMaxSpeed
β 2	Gender	$x7$	Num_Deceleration	$x15$	ΔAvgAcceleration
β 3	Age	$x8$	Avg_Max_Intensity_Index_Train	$x16$	ΔMaxAcceleration
$x1$	Distance	$x9$	Avg_Intensity_Index_Train	$x17$	ΔAvgDeceleration
$x2$	Dist_HSR	$x10$	Avg_StdDev_Intensity_Index_Train	$x18$	ΔMaxDeceleration
$x3$	Dist_SP	$x11$	Avg_Max_Intensity_Level_Train	$x19$	ΔAvg_Intensity_Index
$x4$	Num_HSR	$x12$	Max_Intensity_Level_Train	$x20$	ΔMax_Intensity_Index
$x5$	Num_SP	$x13$	ΔAvgSpeed		

Several different Decision Trees algorithms were tested and showed very positive results, which are presented in the next chapter. Along with the successful results, Decision Trees modelling is appropriate for this research as they are suitable for a classification problem but also allows for a simple conversion to a regression problem, which could perhaps be useful for this investigation. Another factor that had its importance when picking the algorithm to employ, was the possibility to specify misclassification costs to the model. Misclassification costs, which can affect the model and influence the forecast, are essentially weights attributed to certain outcomes. Considering the circumstances, not every prediction in a misclassification scenario has the same consequence. It is distinct to anticipate Red (Fatigued) as an actual observed Yellow (Nearly fatigued) from predicting Green (Not fatigued) as an actual observed Red (Fatigued). To avoid these scenarios, Green/Red (observed/predicted) and Red/Green (observed/predicted) had an increased misclassification cost than the remaining hypotheses. Three different algorithms of decision trees were explored: Random Trees, CHAID and CART.

Accordingly to IBM documentation on Random Trees, Random Trees use trees that mirror CART Trees. These binary trees provide two branches for each splitting field. According to the inner splitting criterion, categories in a categorical field with multiple categories are separated into two groups. The maximum amount of growth is achievable for each tree (there is no pruning). When combining Tree scores, Random Trees use the average or majority vote.

IBM defines the variations between Random Trees and CART Trees from one another in two major ways:

1) In Random Tree nodes, the best predictor from a pool of candidates is used to divide a node at random from the others. CART Tree, in comparison, selects the strongest predictor from each.

2) Random Trees allow each tree to fully develop until each leaf node normally has one record. The depth of the tree may thus be extremely great. Standard CART Tree, however, has several stopping criteria for tree development, which typically results in a significantly shorter tree.

On the other hand, Random Trees enhances CART Tree with two new features:

1) Bagging, which involves sampling with replacement from the original dataset to produce copies of the training dataset. After creating bootstrap samples of the same size as the original dataset, each replica is then used to build a component model. These separate models come together to create an ensemble model.

Only a portion of the input fields is taken into account for the defect measure at each split of the tree.

In order to find the optimal one, many modelling configurations were evaluated (Table 4.4).

TABLE 4. 4: Tested models' parameterization

	Models					
	A	**B**	**C**	**D**	**E**	**F**
Algorithms	**Random Trees**	**CHAID**	**CART**	**Random Trees**	**CHAID**	**CART**
Ensembles	-	-	-	-	Boosting	Boosting
Maximum depth	10	5	10	5	5	10
Misclassification Costs	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 5.

RESULTS

A variety of metrics, that are based on the classification matrix (Grandini et al. 2020) listed in Table 5.1, were used while evaluating the models' quality.

TABLE 5. 1: Example of confusion matrix

		Predicted			
Observed		**Green**	**Yellow**	**Red**	**Total**
	Green	42	5	3	50
	Yellow	2	15	3	20
	Red	3	3	24	30
	Total	47	23	30	100

Following the explanation given by Grandini et al. (2020), accuracy is a summary indicator of how well the model generalizes across the complete dataset. Given the example in Table 5.1, Accuracy would be measured as:

$$Accuracy = \frac{42 + 15 + 24}{100} \tag{5. 1}$$

It is impossible to pinpoint the classes where the algorithm performs worse using this metric, that's why other metrics were applied to evaluate the models' quality, such as Precision, Recall and F1-Score (Grandini et al. 2020). Having in mind that the presented model in this study is a multi-class classification model, calculating these metrics requires handling each class as a single class, independent from the others, to be a Positive class and the others will be considered as Negative classes.

TABLE 5. 2: Quality assessment metrics of classification models

Metric	Formula
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-Score	$2\ .\ (\frac{precision\ .\ recall}{precision + recall})$

Once these metrics have been calculated, an average for each may be computed and used as the model's evaluation results.

For the various timespans proposed, all the evaluated models demonstrated consistent levels of accuracy (Table 5.3). Boosting ensemble accomplished its goals, improving both CHAID and CART's prior performance. If that were the case, it could be possible that different models would be used for the various time periods; nevertheless, Random Trees (model A) stood up as the modelling technique with the highest levels of accuracy across the board.

TABLE 5. 3: Accuracy of the models under test for various predictions over time

	Models					
	A	**B**	**C**	**D**	**E**	**F**
Algorithms	**Random Trees**	**CHAID**	**CART**	**Random Trees**	**CHAID**	**CART**
5 Min Accuracy	82%	76%	80%	65%	79%	77%
10 Min Accuracy	84%	75%	70%	66%	81%	79%
20 Min Accuracy	83%	74%	67%	81%	79%	76%
Average Accuracy	83%	75%	73%	71%	80%	78%

The most significant predictors for model A's predictions throughout the three distinct time periods may be seen in Table 5.4. Half of the 20 variables that are most significant to the models are transversal, however, there’s not a variable that is transversal to all three models. The generated square variables stand out as truly useful to the models from this list of provided variables; 11 of the 20 predictors are obtained from this approach. Additionally, from this table is noticeable the importance of training on fatigue during matches, especially in the 5-Min model where 7 of the 10 most important predictors are somehow related to training sessions. Socio-demographic indicators also had an impact, with CodPos, this reinforces the hypothesis proposed by Bangsbo et al. (2006), which was already discussed in the Literature Review, and Age, demonstrated value for forecasting. On the other hand, speed-derived indicators impacted fatigue, which is consistent with the literature (Mohr et al., 2003, 2008, 2010; Krustrup et al., 2010; Rampinini et al., 2009). 4 out of the 20 most significant predictors are connected to speed. Movements of acceleration and deceleration also had an impact, with 6 of the 20 most important predictors being connected to them.

TABLE 5. 4: Most important predictors for the models

Attribute Variable	Attribute	Importance	5-Min	10-Min	20-Min
β1	CodPos	0.018	0.055		
β3	Age	0.017	0.052		
$x8^2$	Avg_Max_Intensity_Index_Train²	0.009	0.028		
$x9^2$	Avg_Intensity_Index_Train²	0.008	0.025		
$x8$	Avg_Max_Intensity_Index_Train	0.012	0.037		
$x10^2$	Avg_StdDev_Intensity_Index_Train²	0.011	0.032		
$x11^2$	Avg_Max_Intensity_Level_Train²	0.007	0.022		
$x9$	Avg_Intensity_Index_Train	0.009	0.028		
$x10$	Avg_StdDev_Intensity_Index_Train	0.012	0.035		
$x1^2$	Distance²	0.010	0.025		0.005
$x6^2$	Num_Acceleration²	0.011		0.015	0.018
$x3$	Dist_SP	0.003		0.005	0.003
$x15^2$	ΔAvgAcceleration²	0.029		0.047	0.039
$x2$	Num_HSR	0.004		0.007	0.006
$x16^2$	ΔMaxAcceleration²	0.003		0.004	0.005
$x7^2$	Num_Deceleration²	0.013		0.018	0.022
$x13$	ΔAvgSpeed	0.028		0.042	0.043
$x17^2$	ΔAvgDeceleration²	0.021		0.033	0.029
$x14^2$	ΔMaxSpeed	0.003		0.003	0.05
$x18^2$	ΔMaxDeceleration ²	0.001		0.002	

The Model A Classification Matrix for each of the three forecasting horizons is shown below, followed by an analysis of the results using the metrics that were previously presented.

TABLE 5. 4: 5-Min Classification Matrix

		Predicted			
		Green	**Yellow**	**Red**	**Total**
Observed	**Green**	24456	4162	1016	29634
	Yellow	673	8645	1703	11021
	Red	326	2289	14236	16851
	Total	25455	15096	16955	57506

TABLE 5. 5: 10-Min Classification Matrix

Predicted					
		Green	**Yellow**	**Red**	**Total**
Observed	**Green**	25802	2890	942	29634
	Yellow	1195	8153	1673	11021
	Red	480	2267	14104	16851
	Total	27477	13310	16719	57506

TABLE 5. 6: 20-Min Classification Matrix

Predicted					
		Green	**Yellow**	**Red**	**Total**
Observed	**Green**	25552	3452	630	29634
	Yellow	1062	8671	1288	11021
	Red	258	3202	13391	16851
	Total	26872	15325	15309	57506

TABLE 5. 7: Precision - Model A

	PrecisionGreen	PrecisionYellow	PrecisionRed	Average
5-Min	96.08%	57.27%	83.96%	79.10%
10-Min	93.90%	61.25%	84.36%	79.84%
20-Min	95.09%	56.58%	87.47%	79.71%

Precision (Table 5.7) is defined as the proportion of units that our model predicts will be positive and are in fact positive (Grandini et al. 2020). When the Green class was designated as the Positive class, all three models had better outcomes, however, while keeping in mind the objectives set forth for this research, particularly, developing a model that can anticipate fatigue, the Red class should be our Positive class, the results were also extremely promising, exceeding 83% in every forecasting horizon.

TABLE 5. 8: Recall - Model A

	RecallGreen	RecallYellow	RecallRed	Average
5-Min	82.53%	78.44%	84.48%	81.82%
10-Min	87.07%	73.98%	83.70%	81.58%
20-Min	86.22%	78.68%	79.47%	81.46%

Recall (Table 5.8) assesses how well the model can identify every Positive unit in the dataset (Grandini et al. 2020). Recall results, in contrast to Precision results, are better for shorter forecasting horizons when the Red class is taken into account as the Positive class.

TABLE 5. 9: F1-Score - Model A

	F1-ScoreGreen	F1-ScoreYellow	F1-ScoreRed	Average
5-Min	88.79%	66.20%	84.22%	79.74%
10-Min	90.36%	67.02%	84.03%	80.47%
20-Min	90.44%	65.82%	83.28%	79.85%

F1-Score (Table 5.9) aggregates Precision and Recall measures under the concept of the harmonic mean (Grandini et al. 2020).

Averages were calculated for every metric in order to have a better perception of the model as a whole. Accuracy levels were established at around 83%, Precision at 79%, Recall at 81% and finally, F1-Score was 80%.

Figure 5.1 shows an illustration of a model in practice, with the actual classification (Observed) shown initially on the left and afterwards five, ten, and twenty-minute predictive models, respectively.

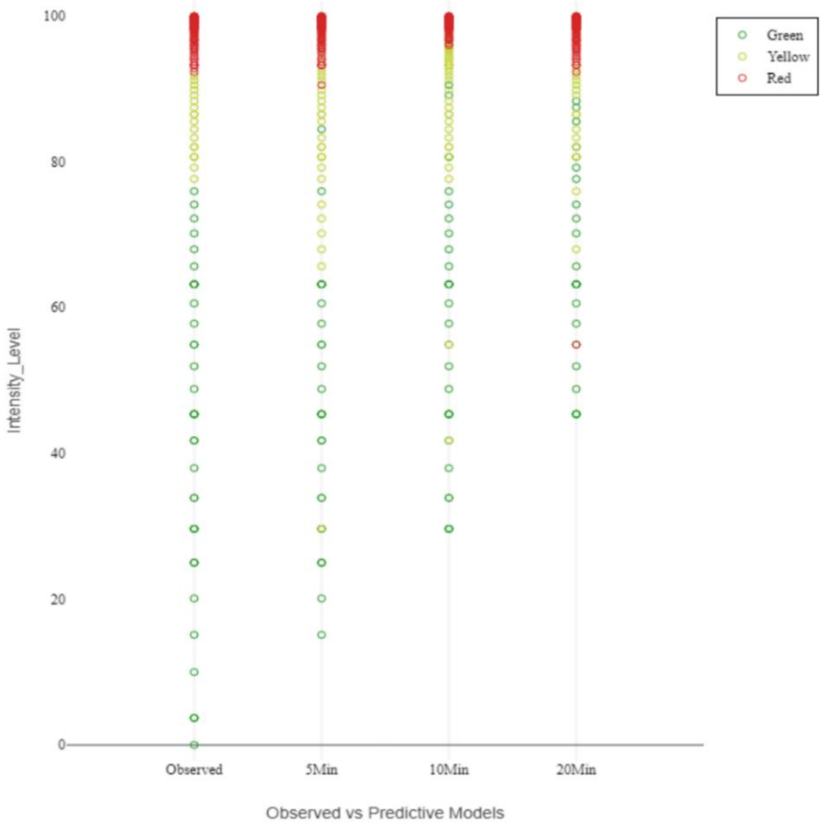

FIGURE 5. 1: Classification Map

Figure 5.2 shows a set of real satellite images produced with the use of the QGIS 3.26.1 software as a preview of the deployment that will follow the models' classification. The colour scheme used on the models can be replicated in this software for a more accurate understanding of Intensity Level progression when combined with actual Global Positioning System coordinates. This image displays a male fullback; despite the fact that his GPS tags are a little all over the place, it is apparent that he is a right fullback. After halftime, the teams switch sides, which justifies the majority of the green tags on the right side of the field representing the first half and the red tags on the left side representing the second half, when fatigue is noticeable.

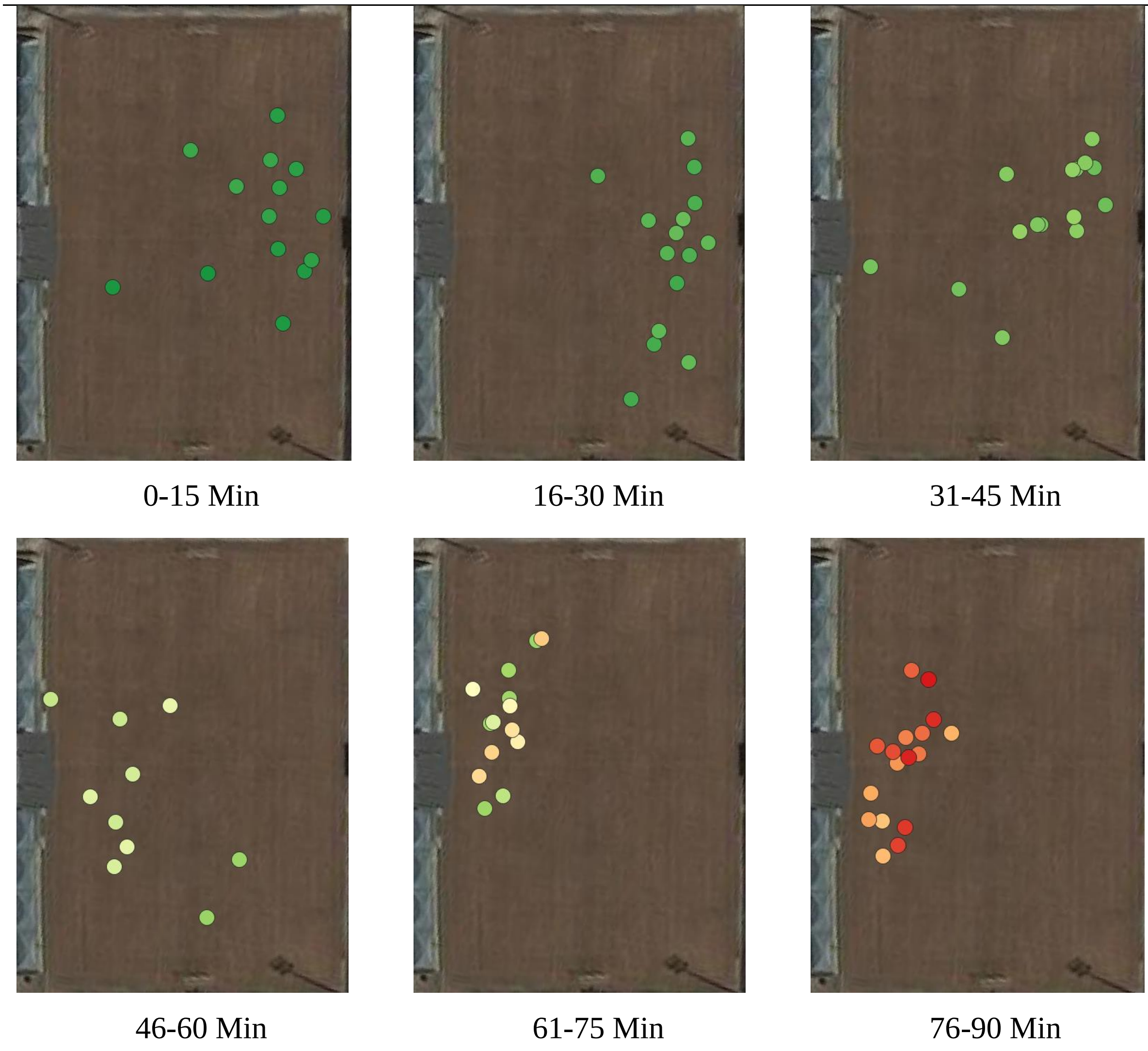

FIGURE 5. 2: On-field classification example using QGIS software (Example 1)

The match's narrative is almost completely depicted in Figure 5.2. The first and second halves are clearly distinguishable from the location marks. When compared to prior positions, the player's location during the 61-75 minute period was lower on the pitch. This could have been a reflection of the first symptoms of exhaustion, as some yellow marks are beginning to appear. However, the team gave up a goal in the last quarter of the match, forcing them to move up the field to chase down the equaliser. This might have raised the physical demands placed on the players, causing fatigue to stop behaving more aggressively and leading to the emergence of more Red marks.

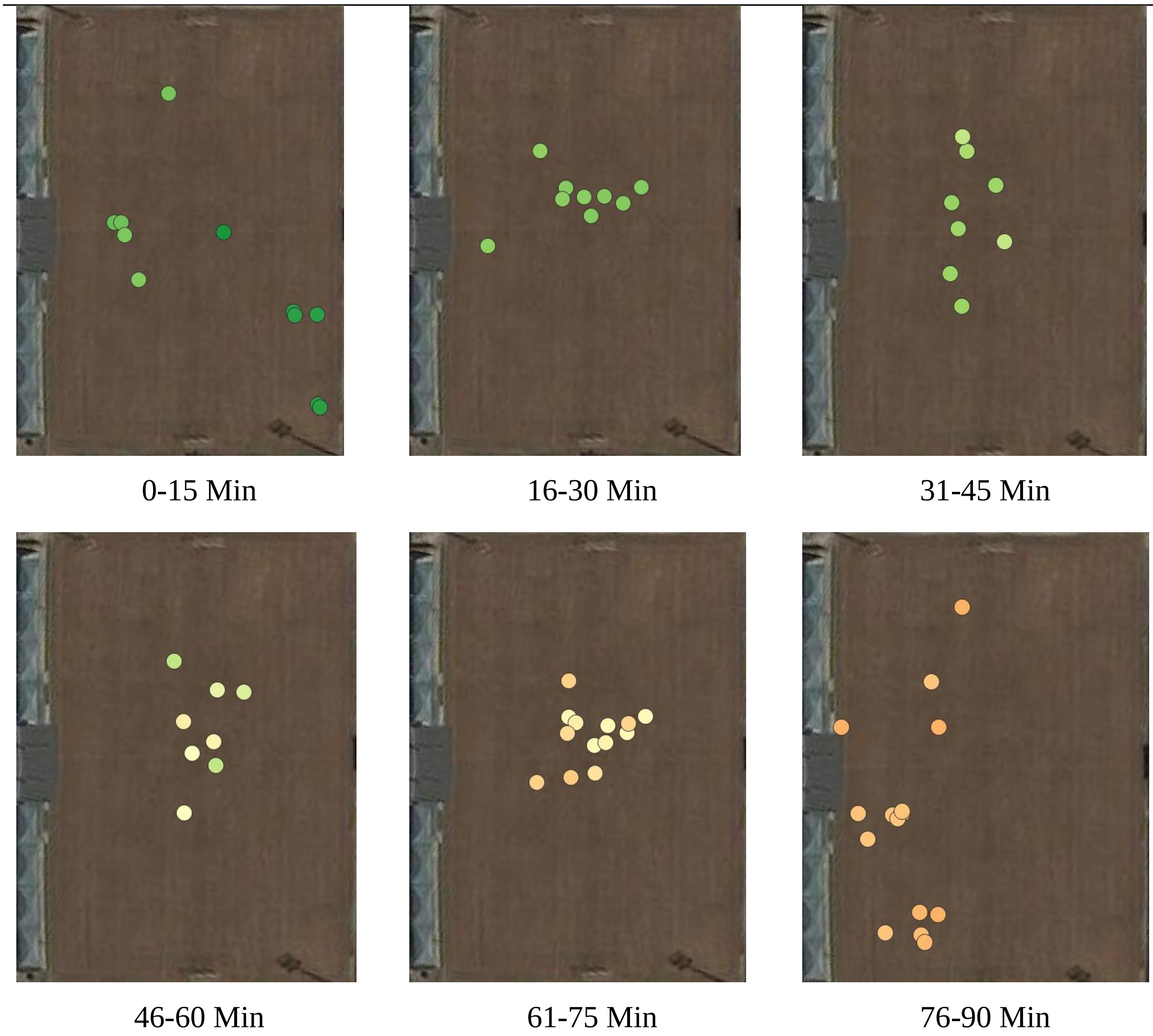

FIGURE 5. 3: On-field classification example using QGIS software (Example 2)

In Figure 5.3, for comparation purposes, another player, in this case a midfielder, that integrated the team that played the match addressed in Figure 3.2. The patterns remain similar, during 61-75min player's positioning seems lower on the field and after conceding in the last minutes of the match, the whole team went up on the field. However, and this has to be emphasised, in this instance the player has not yet achieved the threshold of fatigue specified in this dissertation. This demonstrates that not all players who play the whole 90 minutes are classified as fatigued by the algorithm and that it is possible to distinguish different fatigue levels between different individuals.

The outcomes of this investigation are highly encouraging and might prove to be a tremendously useful tool for real-time application, giving coaches knowledge of their players' degrees of fatigue in anticipation. Academically, the dissertation is said to open up the door for further research projects because it was one of the first—if not the first—to use actual data to create a real prediction model that could be used to assess fatigue.

Chapter 6.

DEPLOYMENT SUGGESTION

Having the model constructed with positive outcomes, it is now time to develop a deployment suggestion.

The recommended deployment in this example will be based on the scenario that we believe is the model's greatest business potential. In our perspective, taking into account the model's capacity to forecast fatigue over three brief time horizons, we recommend that the model be taken into consideration as a real-time tool to be employed during matches in order to assess fatigue and assist the staff in managing their team's degree of exhaustion. There are a few crucial principles to consider in to accomplish this.

1) Assure that an API is available to access the GPS data provider system to be able to transfer data almost instantly. Access to data during the match is essential for success; otherwise, the model won't be able to achieve its primary goal.
2) Having training data is essential since some of the model's input variables are directly derived from training sessions. As a result, a database would be required to store this data.
3) In accordance with the preceding point, as training data is crucial, it is also critical to incorporate GPS devices not only during matches but also during training sessions.
4) The ability to prepare data in line with the model's input is crucial for the model to be deployed successfully.

Before implementing this model, take into consideration these four key aspects.

Now that all the presumptions have been taken into account and validated, a deployment suggestion is made.

This model may be exported as a PMML file, which stands for Predictive Model Markup Language, which enables the implementation of predictive solutions right away. The majority of the most popular commercial and open-source tools support it. Predictive analytic models may be shared between applications and systems thanks to PMML.

Similar to the stages required to create a predictive solution, PMML files, that are standard XML, have a structure that includes: Data Dictionary, Mining Schema, Data Transformation, Model Definition, Outputs, Targets, Model Explanation and Model Verification.

Since the majority of the top commercial and free statistical tools support PMML files, the user has the option to select which software to integrate it with. If the user wants to follow this research methodology so far and keep the deployment in IBM tools, IBM Watson supports it. Alternatively, using an open-source tool, Python could be employed.

Models developed on various platforms can be quickly imported into Python by using the public library Sklearn2pmml.

So, to help clarify, these would be the recommendation for future steps in attempting to put the model into practice:

1. Export the model as a PMML file from SPSS Modeler;
2. Monitor training sessions and keep data from them in a database for later access;
3. Create clear and concise transformation steps to prepare data in accordance with the model's structure;
4. Define α value to determine Intensity_Index and threshold values for Intensity_Level classification;
5. Determine Intensity_Index and Intensity_Level for training sessions so that they can be implemented into the model in the following steps;
6. Keep track of match data;
7. Verify that a GPS data provider system has an API or other integration tool that can transfer data in almost real-time;
8. Apply transformation procedures to data received during the match;
9. Import training session data necessary for model construction;
10. Bring the PMML file in;
11. Execute the model.

Now that the model is operational, the coach and his staff should now take action to better manage players' fatigue.

Chapter 7.

CONCLUSION

Upon completion of the research and writing for this dissertation, one can come to the conclusion that it is possible to establish a framework to create a variable that can support as an indicator of fatigue, while also being possible to adjust this same variable to different contexts, taking into account that it is dynamic, and, consequently, create a high-frequency machine learning model that can predict fatigue with good levels of accuracy in near real-time, during matches, for three different time horizons, allowing coaches and their staff to better manage the physical index values of their players.

From its deployment, managers might truly gain from having what is essentially a virtual assistant to spot fatigued players and players on the verge of being fatigued in the short term. As has already been aforementioned, injuries can arise due to fatigue-related causes (Bengtsson et al., 2013; Tavares et al., 2017) and can restrict players from being available for subsequent matches for weeks or even months. As a result, this framework may not only be useful for identifying fatigue but may also be important for avoiding some injuries, however, this is not the suggested framework's primary objective.

Additionally, it is noted in the Literature Review chapter that players' physical abilities—specifically, their capacity to run and sprint at high rates of speed and cover greater distances in a shorter amount of time—tend to decline throughout the course of the game (Mohr et al., 2003, 2008, 2010; Bangsbo et al., 2005, 2006; Krustrup et al., 2010; Rampinini et al., 2009). Given this, it follows that, under normal circumstances, a player who is fresh and at the peak of their physical capabilities will always be a more valuable asset than a player who is tired. This occurs while only considering the physical aspects of a football game. Given that could exist are more valuable players on the bench than there are on the field, it is the coach's responsibility to make the best decisions in order to set up the team for success. Additionally, keeping in mind the ideas previously discussed in the Study Relevance by Lago et al. (2004) and Barajas et al. (2005), there is a virtual cycle around the relationship between sporting accomplishment and financial success. Therefore, this framework's potential to assist coaches in recognizing fatigue and developing preventive strategies could perhaps help the club achieve better results in both sporting and financial circumstances.

However, these last conclusions are simply based on assumptions; further research is required to establish such conclusions and assess the impact that a framework like this may have on a deployment in the real world.

Chapter 8.

RESEARCH LIMITATION AND FUTURE WORK

The primary conditionings of this study are linked to occurrences with data quality. A data-mature club is necessary for the growth of this type of study in order to obtain better completeness of data. Although training session data was incorporated into the models in this study, not every player's training was reported, which could also have potentially been caused by minor injuries or the player's own absences from the training sessions. However, only 11 players actually had their 5 pre-match training sessions recorded. The outcomes of the models may be improved by this level of completeness. Also related to data quality, Players' Heart Rates (bpm) were correct in just a small number of the .csv that were made available, which could have performed a crucial aspect of the study given that it was made very clear in the Literature Review that Heart Rate is a significant indicator of fatigue.

Although the model developed and presented in this dissertation is intended to forecast fatigue, it's necessary to emphasise that the model is mostly based on physical parameters while underestimating the match environment can be misrepresentative. Players' decreasing trend in various physical attributes might be caused by psychological or even tactical considerations (Mohr et al., 2010), as was previously discussed in the Literature Review chapter. Additionally, incorporating clinical information and other biometric evaluations to the model might increase its usefulness.

Despite the research presented in the Literature Review demonstrated that the GPS units used in this study have good reliability and accuracy, it is important to keep in mind that they might have limitations. Concern has been raised regarding how long the supplier takes to supply the data, which is another GPS issue that has to be addressed if a deployment project for this work is to go forward. If a project is intended to be implemented in a nearly real-time framework but the supplier requires 5, 10, or 30 minutes for data to be able to be delivered, the proposal is made obsolete.

The model results are not necessarily applicable in all situations, which must be noted. When applied to this dataset and this club specifically, the model produced positive results. For different clubs with distinct training methods, match interpretations or player profiles, the model may not provide comparable outcomes.

In the future, rather than conducting research a posteriori as was done in this dissertation, it may be very beneficial to the academy to conduct this type of study with players, include them in the study, and get their input on actually witnessed fatigue.

Another approach is suggested for a similar study for future work as well. Since the focus of this dissertation was on determining if a player will become fatigued in three different short periods of time, estimating how long it will take for a player to become fatigued is another strategy that would undoubtedly be helpful.

Chapter 9.

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