Exploring and Analysing the Notion of Worst Case Scenario in Professional Rugby Union

A thesis

submitted in partial fulfilment

of the requirements for the degree

of

Master of Health, Sport and Human Performance

at

The University of Waikato

by

MORGAN HAAKMA

2020

Abstract

Rugby union is an interval-based contact sport, demanding intermittent bursts of high-intensity running, collisions and impacts. Players need to be conditioned in a way that best prepares them for the demands of the game, and to perform repeated bouts of high-intensity workloads. Understanding the peak periods of 'play' and the 'worst case scenario' (WCS) in rugby union is essential to inform effective training interventions. Through a review of current literature around the notion of WCS and peak periods of play, limitations in existing research methods were identified. Specifically, limitations within the ability of global positioning system (GPS) units to quantify contact and collision workloads, and the error of data recorded over short distances and durations. Limitations within the methodology of fixed-time epochs and rolling-average epochs as a way of quantifying WCS were also explored.

After reviewing the current literature, this thesis encloses an original and innovative study. This research aims to determine a potentially more accurate representation of WCS by quantifying the maximal intensity locomotive demands during 'ball in play' (BIP) for a single play, and across a series of consecutive plays through an innovative rolling-MultiPlay epoch analysis (5 min, 10 min, 15 min, 20 min epochs). This study will also give a contextual indication by identifying the segment of the game in which these maximal workload demands occur.

Data was collected for 51 professional rugby union players over the 2019-2020 seasons. All players wore GPS units (Apex Pro Pod, STATSport, Newry, NIR). All games were filmed and coded through the Sportscode software (Sportscode V8.9, Sportstec, Australia) which was then combined with GPS data from which drills were created for each BIP period. This data was then analysed through a bespoke software where the maximum BIP (MaxBIP) values for a range of GPS metrics were determined for each positional subgroup. A WCS BIP analysis was completed as well as a WCS MultiPlay analysis. Each half of the game was divided into 4 equal segments, and the segments where the MaxBIP values occurred were identified.

Practical applications for indicative training drills for WCS BIP, WCS 5 minute drill, and WCS 20 minute drill are provided. In conclusion, there were no distinct patterns found within the data that suggests the WCS MaxBIP demand could occur in any segment of the game. Therefore, we believe it would be beneficial for players to be conditioned for these peak demands to occur at any stage of the game.

Acknowledgements

I want to take this opportunity to express my deepest gratitude to everyone who has contributed to the completion of this thesis and supported me along the way.

To Greg O'Carroll and the Sir Edmund Hillary Scholarship Programme. Thank you for your continued support throughout my undergraduate degree and to the completion of my Master's Degree. You have supported and mentored me and nurtured my leadership development. I can't thank you enough for the invaluable opportunities you have provided me to progress throughout my time at University. I have gained so much from my time on the Hillary Scholarship, and I will be forever grateful.

To my supervisor, Dr Brett Smith, I can't thank you enough for your level of enthusiasm and dedication to this research. This project presented us with some tremendous obstacles and chances to learn through problem-solving, providing us with some great opportunities to practice resilience. I thank you for your level of expertise, flexibility, patience and understanding throughout the entire process. It allowed me to complete my masters while simultaneously continuing to chase my goals and follow my passion for wakeboarding overseas. We worked with time differences and busy schedules to fit in meetings and zoom calls. Despite technology malfunctions, delays, challenges, and COVID-19, we have made it out the other side. After all, I could not be prouder to submit this work, and I could not have done it without you, so thank you.

I'd like to thank Wayne Smith for backing us and enabling this project to commence. Thank you to the players who participated in this study and to the coaches and management staff for allowing us to conduct this research. I appreciate your efforts with language translation and data collection also. Thank you to the team analyst, James Martin for your attention to detail and your help with this project. Thank you to Andrew Morrissey and David O'Donovan from STATSports for all your help with setting up the software and for helping us solve our various technical problems. I want to say an enormous thank you to Owen Tarrant for your patience and perseverance and dedication to this project. I sincerely appreciate all your help and we couldn't have done it without you.

To the Librarians, Debby and Cheryl, you have both been incredibly helpful. Thank you for helping me understand Endnote, and for spending hours of your time with me to ensure my references and formatting were perfect. I cannot thank you enough.

Thank you to Mum and Dad for your unconditional love and encouragement. Thank you for believing in me in everything I do and for helping me grow to be where I am today.

To my friends and roommates in Orlando, thanks for your help and support throughout my time away, I am so grateful to have had you all to help me manage my life balance between study, wakeboarding and fun. I learned so much from living with you all.

Finally, thank you to Francesco for your love, support, and encouragement. I admire your refreshing outlook on life, and I appreciate you challenging me to think critically and to always strive towards becoming my most authentic self.

Thesis Organisation

This thesis is consists of two chapters. Chapter 1 is a review of literature written in the publication style of a journal article. This review provides the reader with background knowledge of rugby union, time-motion analysis, global positioning systems (GPS) and previous research on the notion of 'worst case scenario' (WCS). Current limitations and gaps in research are highlighted, alongside suggestions for future research. Chapter 2 is our original study which is also written in a publication style of a journal article; therefore, some information in this thesis is consequently repeated. This original and innovative study examines the maximum WCS locomotive workload demands for both 'ball in play' (BIP) time and series of Multi-Play analyses of 5 minute, 10 minute, 15 minute and 20 minute epochs. We also report which segment throughout the game that each maximum value occurs in for each position across a range of metrics. Findings are reported, limitations are discussed, and conclusions are drawn, providing both practical applications and future research recommendations.

Table of Contents

Lists of Tables

Lists of Figures

Abbreviations

Table 1: List of abbreviations

GPS	Global positioning system
WCS	Worst case scenario
BIP	Ball in play
OOP	Out of play
MaxBIP	Maximum ball in play
W: R	Work to rest ratio
%W: R ratio	Percent work to rest ratio
HSR	High speed running
TD	Total distance
Vmax	Maximum velocity
HML	High metabolic load
DISTANCE	Distance
DIST/min	Distance per minute
HSR	High speed running
HSR/min	High speed running per minute
SPRINT	Sprint distance
SPRINT/min	Sprint per minute
HMLD	High metabolic load distance
HMLD/min	High metabolic load distance per minute
ACC	Acceleration
ACC/min	Acceleration per minute
SEE	Standard error of estimates

1 Chapter One
Literature Review

1.1 Introduction:

Rugby union is an interval-based sport, typically consisting of two 40-minute halves (Duthie, Pyne, & Hooper, 2003a), separated by a half time break of 10-15 minutes (Laws of the Game Rugby Union). Rugby demands collisions, contact, skill, high speed running, tactical thinking and decision making. Commonly, periods of high-intensity efforts typically lasting <4 seconds, and low-intensity efforts, are separated by short periods of rest, commonly lasting around 5-20 seconds (Austin, Gabbett, & Jenkins, 2011; Cunningham et al., 2018; Duthie, Pyne, & Hooper, 2005; McLean, 1992; Roberts, Trewartha, Higgitt, El-Abd, & Stokes, 2008; Thornton, Nelson, Delaney, Serpiello, & Duthie, 2019). McLean (1992) recognised that the "density of physical work" (p. 286), and the pattern of work to rest ratios (W: R), are of equal, if not greater importance than traditional measures such as velocity, duration, and distance covered running when quantifying physical demands of players. In some cases, players are required to perform repeated high-intensity bouts for numerous consecutive plays, requiring specific training to condition players for continued high performance and accuracy (Duthie et al., 2005). Rugby is a continually evolving sport, and since becoming professional in 1995, there has been an increased demand for scientific knowledge to quantify the contemporary demands of competition. It is crucial to understand these demands in order to effectively train players to perform at their peak (Austin et al., 2011; Cahill, Lamb, Worsfold, Headey, & Murray, 2013; Cunningham et al., 2018; Duthie et al., 2003a, 2005; Eaton & George, 2006; Pollard et al., 2018; Reardon, Tobin, Tierney, & Delahunt, 2017; Sheppy et al., 2020).

During match-play, 2 teams of 15 players compete for the most points (World Rugby, 2019), and the ability for players to work harder for longer than the opposition is advantageous. A try is worth 5 points, a conversion is worth 2 points, a penalty try is worth 7 points, and a penalty goal and dropped goal are both worth 3 points (World Rugby, 2019). Since becoming professional, law changes within rugby union have been made. These law changes were intended to keep the game "attractive to spectators" (Austin et al., 2011, p. 259), competitive with other football codes (Austin et al., 2011; Duthie et al., 2003a), improve safety and increase continuity for better competition (Williams, Hughes, & O'Donoghue, 2005).

The anaerobic energy system is said to be the primary energy system used when performing high-intensity bouts, although players also require an adequate level of aerobic conditioning to aid recovery between high-intensity efforts (Duthie et al., 2005; McLean, 1992). According to Duthie et al. (2003a), “repeated high-intensity sprints” (p. 974), as well as tackles, scrums, lineouts, rucks, and mauls involved in the game require players to be proficient in “endurance, speed, agility, power, flexibility and sport-specific skill” (p. 983).

1.2 Physical Demands of Professional Rugby Union Players

Player workload demands in rugby continue to evolve, with advancements in technology offering easier ways to measure and quantify workloads (Theodoropoulos, Bettle, & Kosy, 2020). Therefore, researchers need to continually update the knowledge around physical and physiological demands of rugby union players by quantifying workloads and reviewing and validating methodologies.

Duthie, Pyne, Marsh, and Hooper (2006) determined the sprint requirements of elite rugby union players in training and competition. They claimed that the speed at which players are running at the commencement of the sprint has an evident impact on the time it takes them to reach percentages of maximum velocity (Vmax) (Duthie et al., 2006). They combined this knowledge with video-based time-motion analysis in order to estimate velocities reached by players during the game. It was discovered that backs performed more high-velocity sprints (>90% Vmax) than forwards, highlighting the greater importance for backs to display Vmax qualities compared to the forwards. The researchers concluded that sprint-training programs need to be focused around “developing acceleration qualities for all playing positions” (p. 212), as well as incorporating Vmax sprints (Duthie et al., 2006). Training recommendations were made for the forwards to focus on accelerations from a slow-moving or standing start, and backs to work on sprints from standing starts as well as transitioning from jogging starts at various speeds to sprinting, to prepare for game day demands (Duthie et al., 2006).

Austin et al. (2011) described match-play demands of professional, super rugby union players through a time-motion analysis to quantify the movements of super 14 players during the 2008 and 2009 seasons. They found an increase in time spent in “high intensity running activities; sprint frequency, and work to rest rations” (p. 262) across all playing positions when compared to previous work done by Duthie et al. (2006), Eaton and George (2006) and Roberts et al. (2008) (as cited in Austin et al., 2011). When comparing the work of Austin et al. (2011) to that of Duthie et al. (2005), there was an evident increase in the number of sprints performed, with both studies using similar analysis methodology.

Austin et al. (2011) presented findings that during the 2008 and 2009 seasons, players spent "7% less time standing, 4% less time jogging, but 4% more time striding, 2% more time sprinting and 2.5% more time in non-running intense activities" (p. 262), compared to the study by Duthie et al. (2005) on super 12 players during the 2000 and 2001 seasons (as cited in Austin et al., 2011). This increase in the physical demands of players is further emphasised when comparing the time spent "striding, sprinting, tackling or scrummaging" (p. 262) in research by Austin et al. (2011), to studies completed by Eaton and George (2006) and Roberts et al. (2008) (as cited in Austin et al., 2011). It is, however, acknowledged that differences in findings could be influenced by interpretations of the law and methodological differences (Austin et al., 2011). Reardon et al. (2017) also found an increase in general intensity and pace when analysing average performance demands compared to previous research completed by Cahill et al. (2013) (as cited in Reardon et al., 2017). Therefore, further research into the contemporary demands of rugby players is needed and notions such as WCS need to be explored further.

1.3 Time

Time is an important contextual factor when researching rugby, specifically 'ball in play' time (BIP), and the length of time 'out of play' time (OOP), or the 'rest period'. It is essential to distinguish the difference between BIP time and OOP time as they influence the analysis and interpretation of locomotion values, as well as potentially influencing transient fatigue levels in players. 'Ball in play' is defined as when the player is in possession of the ball and either team can contest for the ball (Williams et al., 2005) until the ball goes out or the referee orders a stoppage. 'Out of play' is considered to be the period from when the referee has stopped the play, until the next play starts (Williams et al., 2005).

During the full 80 minutes of the match time, the average BIP time is approximately 30 minutes in total (Duthie et al., 2003a; McLean, 1992; Williams et al., 2005), with the remaining time being taken up by conversions, penalty kicks and other times when the ball is OOP (Duthie et al., 2003a). Game time can be stopped for a variety of reasons, such as consultation between officials, injuries, and when the ball has already gone dead (World Rugby, 2019). Time can also be paused for substitutions, clothing amendments, and retrieving the ball (World Rugby, 2019). According to McLean (1992) (as cited in Duthie et al., 2005), lengthy stoppages are usually for goal kicks or because of an injury, resulting in the mean rest duration increasing to "between 35 and 95s" (Duthie et al., 2005, p. 529). However, a frequency distribution showed that the majority of rest periods were "less than 20s in duration" (Duthie et al., 2005, p. 529). Duthie et al. (2005) state that "extended rest periods during conversions and penalties have a significant influence on the mean rest duration" (p. 529), which could potentially impact transient fatigue.

1.4 Time-Motion Analysis

Due to the physical nature of rugby, it is incredibly challenging to take intrusive physiological data, such as blood sampling (Roberts et al., 2008). Therefore, time-motion analysis was the preferred method for quantifying the total time players spent doing each activity and quantified the frequency of movement patterns, activity levels, velocities, distances, levels of exertion and W: R (work to rest) ratios, (Duthie et al., 2003a; Duthie, Pyne, & Hooper, 2003b; Duthie et al., 2005; Duthie et al., 2006; Roberts et al., 2008).

Duthie et al. (2005) used time-motion analysis to quantify the movement patterns of players from three Australian provincial super 12 teams, examining the differences between positional groups and 1st and 2nd halves during 16 games in 2001 and 2002. They filmed each player for the entire duration of the game, including all breaks in play except the half-time break. They found that when comparing movement patterns of players in the 1st half to the 2nd half, there was no significant difference between them. They, therefore, concluded that fatigue, although most probably felt by the players, did not cause an overall decrease in activity levels between halves (Duthie et al., 2005). Duthie et al. (2005) concluded that in order to understand the demands and workloads of players, the ability to measure locomotive metrics accurately is crucial, alongside accurate quantification of contacts and collisions.

Roberts et al. (2008) assessed the "physical demands of elite English rugby union using an accurate and reliable objective time-motion analysis technique" (p. 826). Player fatigue was said to be shown by the "amount of high-intensity activity performed by the players during progressive periods of the match" (Roberts et al., 2008, p. 826). Therefore, changes in activity patterns throughout the game were analysed to identify if there was a decrease in the high-intensity activity performed by players (Roberts et al., 2008). The greatest distance covered in play was during the 1st 10 minutes of the game; however, it was said that majority of this was at a lower-intensity, whereas high-intensity activity remained relatively constant for the duration of the game (Roberts et al., 2008). Running backwards was not quantified in this study, which according to Roberts et al. (2008) could potentially expend more energy than running forwards and may have had an impact on player's fatigue levels, potentially posing a limitation to this study.

Time-motion analysis does not accurately measure or accommodate commencement speed of sprints, which is said by Duthie et al. (2006) to have a significant effect on the maximum speed achieved during a sprint. Duthie et al. (2003a) declared that time-motion analysis is vulnerable to human measurement error. There are also limitations with the validity of a time-motion analysis, due to the categorisation of movement patterns, as in the game, players are required to perform a "dynamic combination of tasks, skills and tactics" (p. 983). Furthermore, bouts of static exertion are especially important phases of rugby and make a significant impact on the outcome of the game (Roberts et al., 2008). However, time-motion analysis is said to be limited in its ability to quantify the intensity of static exertion phases, as it is too technically challenging (Roberts et al., 2008). At the time of these studies (Duthie et al., 2003a, 2005; Duthie et al., 2006; Roberts et al., 2008), players did not wear GPS devices, and this would have made it near impossible to accurately quantify or measure locomotive demands, therefore posing further limitations to these studies.

1.5 Global Positioning Systems

Many team sports utilise global positioning system (GPS) units with accelerometers as a measuring and monitoring tool for positional demands, such as velocity, and overall movement patterns during training and competition (Akenhead, French, Thompson, & Hayes, 2014; Cummins, Orr, O'Connor, & West, 2013; Malone, Barrett, Barnes, Twist, & Drust, 2020; Naughton et al., 2020; Reardon et al., 2017; Theodoropoulos et al., 2020). The GPS unit's ability to capture live data is said to allow monitoring and adjustments of workloads during training in order to optimise performance, prevent injuries, and ensure players are not overtraining or undertraining for the demands of competition.

GPS units are often used in research to quantify player workloads and demands, aiding practitioners in tailoring training programs in a way that adequately prepares players for the demands of competition, and to perform at their best (Cummins et al., 2013). The integration of triaxial accelerometers within GPS units allows for work rate and physical load information to be collected, and GPS units with a higher frequency rate are said to provide a greater validity for measurement of distance, according to Cummins et al. (2013). Although some GPS units have tackle detection technology, they are only able to detect tackles. They cannot "distinguish between the types of tackles" (Cummins et al., 2013, p. 14), limiting their ability to quantify tackle or collision loads (Naughton et al., 2020). At the time of their study, Cummins et al. (2013) acknowledged that the only way to analyse collision and tackle events was to "manually label impact data through cross referencing video footage with the GPS and accelerometer measurements" (p. 14).

Kelly, Coughlan, Green, and Caulfield (2012) explained that "after a collision occurs, large rapid variations sometimes occur in the acceleration signal" (p. 83), and "other times there is no noticeable change to the signal after the tackle" (p. 83). This rapid variation makes it hard to understand what has occurred from analysing data from the GPS unit only. Roe, Halkier, Beggs, Till, and Jones (2016) highlighted that collision and impact activities "involve minimal horizontal displacement" (p. 591) posing limitations in the ability of GPS units to quantify these important aspects of the game.

Akenhead et al. (2014) examined the "acceleration-dependent criterion validity and inter-unit reliability of Catapult S4 10HZ GPS receivers" (p. 565), and their ability to measure instantaneous velocity. It was reported that the validity and inter-unit reliability of these GPS units was "inversely related to acceleration" (p. 565) "with greater acceleration reducing the validity and reliability of velocity measurement" (Akenhead et al., 2014, p. 565). It was reported that accuracy is compromised in accelerations of over $4m.s^{-2}$ when using the "Catapult S4 10Hz model of GPS" (p. 565) and that using this model of GPS "may be unsuitable for the measurement of instantaneous velocity during high magnitude ($>4m.s^{-2}$) accelerations" (Akenhead et al., 2014, p. 565).

Howe, Aughey, Hopkins, Cavanagh, and Stewart (2020) quantified the peak periods of rugby union and determined the "sensitivity, reliability and construct validity of measures derived from a wearable device incorporating GPS and accelerometer technology" (p. 1). They collected data from both elite and sub-elite rugby union players and used a rolling-average methodology. Like Akenhead et al. (2014), the Catapult 10HZ GPS (OptimEyeTM S5 GPS, firmware version 7.22, Catapult Sports, Melbourne, Australia) was also examined in this study. Howe et al. (2020) reported that this GPS unit has "poor sensitivity for quantifying peak movement across all epochs" (p. 1) of 5-600 seconds, as "all measures displayed correspondingly low reliability across most epochs" (Howe et al., 2020, p. 1). Construct validity was found to be "evident in mean differences between positions and halves" (Howe et al., 2020, p. 1). A within-subject variation was used to determine 'noise', and large errors (poor sensitivity) from the signal to noise ratio were calculated (Howe et al., 2020). Howe et al. (2020) concluded that "rugby union players need to be monitored across many matches to obtain adequate precision for assessing individuals" (p. 1). Practitioners are recommended to use GPS and accelerometers alongside each other to monitor and prescribe training that represents match intensities (Howe et al., 2020).

It appears that during data collection, the accuracy of GPS data fluctuates as the distance covered changes (Smith & Hopkins, 2012). According to Castellano, Casamichana, Calleja-González, Román, and Ostojic (2011), research using more modern GPS unit technology has shown considerable improvements in accuracy since the older 1-5 Hz GPS units, which have recorded a high standard error of estimates (SEE) (~25% for 10m, ~10% for 40m and ~ 2% for 500m) (Smith & Hopkins, 2012). There remain concerns around the accuracy of GPS data, despite these improvements in technology to date, especially during rugby specific movements such as side-stepping, swerving and zig-zagging (Jennings, Cormack, Coutts, Boyd, & Aughey, 2010). According to Smith, Tarrant, and McIntosh (2019), there is evidence that the longer the duration of the GPS data collection, the more accurate it is. This may potentially be due to the normally distributed errors, implying that the longer the duration being measured is, the greater the opportunity provided is for the negative errors to be cancelled out by the positive errors.

1.6 Worst Case Scenario/ Peak Demands

It is critical to accurately quantify the locomotive workload demands of peak periods of gameplay in order to understand the 'worst case scenario' (WCS) requirements of players and to adequately prepare them. The notion of WCS has previously been considered as either the "single longest bout of uninterrupted gameplay" (Reardon et al., 2017, p. 3) or the peak period of play. WCS has commonly been analysed using either a rolling-average method (Delaney et al., 2017; Owen, 2019; Read et al., 2019) or fixed-time method (Carling & Dupont, 2011; Jones, West, Crewther, Cook, & Kilduff, 2015).

Cunningham et al. (2018) and Sheppy et al. (2020)'s compared the use of rolling-average and fixed-time methodologies to quantify what was thought to be the peak period of the game. Using a fixed-time period method of analysis likely underestimates the player's demands due to the risk that the most intense phase of play does not necessarily fall into one pre-defined period (Cunningham et al., 2018; Sheppy et al., 2020). Therefore, using a rolling average methodology has been the preferred method of analysis over fixed-time methods, due to the potential for "loss of sampling resolution associated with the windowing of data over fixed periods" (Cunningham et al., 2018, p. 1). However, the importance of distinguishing and isolating ball-in-play time (BIP) from out of play time (OOP) for analysis purposes has become more prevalent in research regarding WCS and peak demands (Pollard et al., 2018). Whitehead, Till, Weaving, and Jones (2018) carried out a systematic review of the use of microtechnology to quantify the peak match demands of football codes. It was stated that "the most intense periods of play often occur at critical periods of match play" (Whitehead et al., 2018, p. 2551), which reinforced the importance of adequately preparing players for the 'peak' periods of the game.

1.6.1 Single Longest Bout of Play

A study was conducted by Reardon et al. (2017) using a combination of "GPS and video analysis to establish the locomotor and collision demands of the WCS" (p. 3). They analysed the "single longest bout of uninterrupted gameplay" (p. 3) and analysed differences in positional groups across a series of games (Reardon et al., 2017). Reardon et al. (2017) found a statistically significant difference between positional groups when analysing total distance (TD), maximum velocity (Vmax), walking distance, low-speed running, high-speed running (HSR), sprint efforts, and collisions. Conclusions were drawn that the WCS does not necessarily occur during the same play for all positions (Reardon et al., 2017). WCS demands, defined in this study as the "single longest duration bout of ball-in-play time" (p. 3), involved mostly low-intensity activity mixed with "intermittent bursts of high-intensity collision and running activity" (Reardon et al., 2017, p. 6). However, defining WCS as "the single longest period of continuous play" (Reardon et al., 2017, p. 8), is limiting, as more recent research has suggested that maximal work demands, deemed as WCS, are likely to occur in shorter plays (Peeters, Carling, Piscione, & Lacome, 2019; Pollard et al., 2018). Whitehead et al. (2018), Owen (2019) and Delaney et al. (2017) have all concluded that the longer the duration period being analysed was, the lower the intensity appeared "due to the physiological, contextual and technical-tactical demands of the sport" (Whitehead et al., 2018, p. 2571). Overall, this research suggested that using a rolling-average methodology of shorter durations was likely best practice.

1.6.2 Fixed-Time Methodology

Jones et al. (2015) quantified "positional and temporal movement patterns of professional rugby union players" (p. 488) through a fixed-time epoch methodology, using averages across each period. They analysed each half of the game from fixed-time periods of 10 minutes and excluded any overtime played >40 minutes for each half. They found significant differences between positional groups and sub-positional groups in "player load, cruising and striding between halves" (p. 488), with a decline throughout both halves of high and low-intensity movements, accelerations and decelerations (Jones et al., 2015). A limitation of this study is that they may have missed important maximal data from what was excluded in overtime.

Carling and Dupont (2011), examined the relationship between a decline in physical performance and skill-related performance in professional soccer which was seemingly analysed using a fixed-time period method. Carling and Dupont (2011) acknowledged the influence BIP time had on the player's running workloads, as well as the number of opportunities they had to play the ball compared to other fixed-time periods. Distinguishing BIP time from OOP time is essential, as Carling and Dupont (2011) found that the ball was in play for a significantly greater time during the first 5 minutes of play compared to the last 5 minutes. It was acknowledged that the difference in BIP time potentially influenced player's workloads and provided unequal game related opportunities across all 5 minute periods (Carling & Dupont, 2011), which would likely be the same across most team sports.

The intermittent nature of rugby means that games do not all follow the same sequence of events, nor do these events last the same duration. Therefore, it is crucial to distinguish the work done during BIP time from OOP time. It has been said that including OOP time has the potential to significantly influence and underestimate the average performance demands during a game (Carling & Dupont, 2011). For example, it is likely that backs have a greater repositioning movement than the forwards in OOP time (Pollard et al., 2018), which would increase performance monitoring metrics such as the TD covered. These heavy repositioning workloads during OOP time, however, could pose possible limitations to any studies excluding OOP time from their analysis. Therefore, while peak-period and WCS game data appear to be more accurately quantified through analysing BIP time, repositioning work during OOP time may be worth quantifying also.

1.6.3 Rolling-Average Methodology

The ability to quantify the peak periods of match-play is said to give insight into the intensity in which drills should be completed during training for players to be adequately prepared for the game (Owen, 2019). Owen (2019) completed a peak-period analysis through a moving-average methodology, aimed at quantifying locomotive and contact loads. Positional groups and subgroups, including tight and, loose forwards, and inside and outside backs, over ten varying durations (1min, 2min, 3min, 4min…10mins long) were analysed to understand the maximum workload demands, in comparison to whole game averages, which have previously said to underestimate the most intense periods of play (Cunningham et al., 2018; Varley, Elias, & Aughey, 2012; Whitehead et al., 2018). Overall, the forwards were reported to move at a lower intensity and a "significantly slower relative distance than the backs during the peak periods of play for all moving-average durations" (Owen, 2019, p. 97). The forwards were reported to have significantly different ($P < 0.05$) relative distance values from one rolling-average segment to the next between the 1 minute to 6 minute durations (Owen, 2019). In comparison, the backs reported significantly different ($P < 0.05$) relative distance values from one rolling-average segment to the next between the 1 minute to 7 minute durations (Owen, 2019).

In a study by Read et al. (2019), a 0.1 second rolling-average methodology was employed to quantify the maximum running intensities of English academy level rugby union. They examined 9 different time durations (15s, 30s, 1min, 2min, 2.5min, 3min, 4min, 5min, and 10min). In alignment with conclusions drawn by Delaney et al. (2017), Whitehead et al. (2018) and Owen (2019), Read et al. (2019) found that running intensity decreased as the time increased and that for all durations, the backs had a greater running intensity than the forwards, which is a common finding across most recent studies. Delaney et al. (2017) suggested that contextual knowledge of the workload demands before and after the 'peak period' would likely be beneficial to coaches and trainers when preparing their players for the most demanding passages of play. Therefore, this could be helpful for future researchers to consider.

1.6.4 Fixed-Time Vs. Rolling-Average Methodologies

Cunningham et al. (2018) completed a study which compared the use of the rolling-average method and fixed-time epoch method to quantify the "peak movement demands of international rugby union match-play" (p. 1) to gain more insight into the WCS for each position during the competition. Players were monitored for peak values of HSR with a threshold of >5 $m{\cdot}s^{-1}$, and relative distance covered ($m{\cdot}min^{-1}$) over 60-300 seconds.

Sheppy et al. (2020) also completed a study comparing rolling-average and fixed-time epoch methodologies to "assess the duration-specific worst-case scenario locomotor demands" (p. 609), examining TD, relative distance, and HSR (>4.4$m.s^{-1}$). Epochs of 60 second increments were specified to give a range of fixed-time and rolling-average durations from 60-600 seconds, and distances were recorded for the total match and each full half (Sheppy et al., 2020).

In conjunction with findings by Reardon et al. (2017), both Cunningham et al. (2018) and Sheppy et al. (2020) discovered that regardless of the method used, as the epoch length increased, the distance covered or HSR distance decreased for the entire team, forwards, and backs. Overall, it is apparent that the fixed-time methodology underestimates both HSR and TD, regardless of the epoch duration (Cunningham et al., 2018; Sheppy et al., 2020). Sheppy et al. (2020) reported the fixed-time methodology "underestimated the WCS TD by ~8-25% and HSR by ~10-26% depending on epoch length and playing position" (p. 611). Further emphasising the error associated with fixed-time methodologies, it was also reported that the HSR demands increased for the backs in comparison to the front row, when presented as rolling-averages, compared to fixed-time (Cunningham et al., 2018). Sheppy et al. (2020) found that the forwards and backs covered similar total distances throughout the entire match, reporting reductions in distance covered in the 2nd half when compared to the 1st half. In contrast, Cunningham et al. (2018) concluded that backs travelled a greater HSR distance and TD when compared to the forwards in both fixed-time and rolling-average methods (Cunningham et al., 2018). These findings were said to offer insight into the WCS running demands, providing coaches with information to inform training and aid in training specificity for each position to prepare for the most demanding passages of play (Cunningham et al., 2018; Sheppy et al., 2020).

1.6.5 Ball in Play Vs. Whole Match Averages

Pollard et al. (2018) quantified the demands of international rugby union using GPS software to analyse the mean BIP, maximum BIP (MaxBIP), and whole match average outputs (Pollard et al., 2018). The high metabolic load (HML) and high speed running (HSR) values were significantly lower in the average whole match analysis compared to the mean BIP and MaxBIP analysis (Pollard et al., 2018). It was also reported that for both mean BIP and MaxBIP, the forwards were involved in more collisions than the backs, while the backs performed more HML and HSR compared to the forwards (Pollard et al., 2018). Overall, it was evident that all BIP metrics were significantly higher than whole match metrics (Pollard et al., 2018), therefore reinforcing the importance of BIP analysis, as not to underestimate the peak demands of gameplay.

1.6.6 Temporal Pattern Analysis

According to Owen (2019) and Jones et al. (2015), knowledge of the "pacing strategies employed" (Owen, 2019, p. 9) and understanding the position-specific areas of fatigue experienced throughout the game, can help decisions be made for ideal substitution times. Owen (2019) completed a temporal pattern analysis to identify "position-specific demands as the match progresses" (p. 9). Games were split evenly into 8 periods of roughly 10 minutes each, and metrics were compared between segments of the game, which identified "fluctuations in player performance" (Owen, 2019, p. 31). The 1st quarter of each half had the "most intense running demands of the match" (p. 102) and both forwards and backs covered significantly more distance in match periods 1 and 5 compared to all other periods ($P < 0.05$) (Owen, 2019). Match period 1 showed a more considerable distance covered compared to match period 5, although it was not deemed a significant difference ($P > 0.05$) (Owen, 2019). It was also reported that backs covered significantly less distance in match period 4 than they did in match period 2 (P = 0.0-1) (Owen, 2019). Although it is beneficial to know the distances of positional groups and sub-positional groups travelled within these eight periods, it would be helpful for researchers to quantify which segment of the game that the peak numbers are recorded for a broader range of metrics.

1.6.7 Common Limitations

There are a few common limitations to most of these studies. Delaney et al. (2017), Read et al. (2019), Owen (2019), Cunningham et al. (2018) and Sheppy et al. (2020) all included OOP time as part of their analyses. The potential limitation with this is that rugby, among most football codes, does not typically follow the same sequence of activities, and there are not always equal amounts of BIP time and OOP time in each game. Since a greater amount of work is usually required in BIP time compared to OOP time, this could be a limiting factor when using results to inform training.

Another common limitation is in some studies, only the data from players who had played ≥60 minutes of match play were included. This is limiting, as analysts may have missed maximum metric values achieved throughout the game, potentially causing an inaccurate representation of the WCS. Lacome, Piscione, Hager, and Carling (2016) analysed the long-term contribution of substitute players in comparison to those who played the entire match and substituted players. A trend was found for a "greater running performance in both forward and back substitutes over their entire match-participation time" (Lacome et al., 2016, p. 791). Another trend was found for a greater short-term running performance over the first 10 minutes compared to their final 10 minutes of play (Lacome et al., 2016). This was compared to those who played the entire match or those who were replaced (Lacome et al., 2016). Pollard et al. (2018), Jones et al. (2015), and Sheppy et al. (2020) quantified peak demands for players who had played >60 minutes, however, Lacome et al. (2016) suggests that substitute players have the potential to reach the maximum performance demands of the game. Therefore, it may be beneficial to include all players in future WCS and peak-demands research in rugby union.

While some studies seemingly analysed accelerometry data such as collisions, there are several limitations within a GPS unit's ability to quantify locomotive collision data accurately, as previously stated (Cummins et al., 2013; Kelly et al., 2012; Naughton et al., 2020; Roe et al., 2016). However, due to this, a number of these studies only analyse locomotion workloads and do not account for a significant proportion of match play including "nonlocomotory activity such as jumping, pushing, pulling, and wrestling" (Delaney et al., 2017, p. 1044). Greater advancements in the technology's ability to measure collisions, impacts, and static exertion would be extremely beneficial to understanding player workloads and demands.

1.7 Training Specificity

The concept of training specificity is fundamental in rugby and has been widely recognised as a necessity when training elite rugby athletes (Austin et al., 2011; Cunningham et al., 2018; Deutsch, Kearney, & Rehrer, 2007; Duthie et al., 2003a, 2005; Duthie et al., 2006; Owen, 2019; Roberts et al., 2008). Movement data recorded during the game is used for comprehensive analysis, giving coaches a better understanding of the demands that players face during the game, which they then use to inform training sessions (Duthie et al., 2005). It is crucial to specifically tailor training and fitness testing to focus on position-specific demands, especially activities involving static exertions and high-speed running, as opposed to only focusing broadly on forwards and backs (Austin et al., 2011; Deutsch et al., 2007; Duthie et al., 2005). The most considerable positional difference between game demands and physical characteristics is between the forwards and backs (Duthie et al., 2003a; Duthie et al., 2006). However, Deutsch et al. (2007) highlight the importance of focusing on the smaller positional groups, as they have individual requirements and specific game demands that can differ from others.

Generally, contact demands, collision activities and static exertion activities are more frequently required by the forwards in comparison to the backs, who are more frequently required to perform higher locomotive demands (Cahill et al., 2013; Owen, 2019; Roberts et al., 2008). Therefore during training, emphasis should be placed on acceleration from a standing start for the forwards, compared to the backs who need to change between jogging and sprinting efficiently (Duthie et al., 2006).

It is commonly accepted that the backs tend to perform a higher frequency of sprinting and endure longer sprinting efforts, covering a greater TD during the game compared to the forwards (Duthie et al., 2003a; Duthie et al., 2006; Eaton & George, 2006; Roberts et al., 2008). A large volume of sprint training is essential for the backs, and it was recommended by Duthie et al. (2006) that "sprinting efforts should be performed from a variety of starting speeds to mimic the movement patterns of competition" (p. 208). Duthie et al. (2003a) claimed that backs sometimes have extended rest periods between high-intensity efforts compared to the forwards. Deutsch et al. (2007) also identified some differences between smaller positional groups, claiming that "outside backs tended to specialise in the running aspects of play" (p. 461), while the "inside backs tended to show greater involvement in confrontational aspects of play such as rucking/ mauling and tackling" (p. 461).

Players are often required to perform repeated high-intensity efforts with only short rest durations between plays during the game. Therefore, in order for the players to be best prepared for this in the games, it needs to be applied during conditioning training (Duthie et al., 2003a, 2005). Duthie et al. (2006) claim that some aspects of training are equally important for all positions. In particular, they found similarities in the "relative distribution of velocities achieved during competition for forwards and backs" (p. 208) implying that it is beneficial for everyone to "train acceleration and Vmax qualities" (Duthie et al., 2006, p. 208).

According to Duthie et al. (2003a), the forwards need to focus on the "higher work rates of the game" (p. 974). Deutsch et al. (2007) highlighted the difference between smaller positional groups, distinguishing front-row forwards from loose forwards. Usually, the front-row are involved in activities concerning "gaining/retaining possession" (p. 461). The loose forwards usually play a more "pseudo back-line role" (p. 461), involved in more "aspects of broken play such as sprinting and tackling" (p. 461) and "less rucking/mauling" (p. 461) than the front-row forwards. Quarrie and Wilson (2000) (as cited in Reardon et al., 2017) stated that "prop forwards produce more force when scrummaging compared to locks and back-row forwards" (p. 9). Roberts et al. (2008) concluded that forwards spent more time in static exertion high-intensity activity than the backs. The backs, however, had covered a higher TD than forwards, due to distance covered walking and running at high-intensity (Roberts et al., 2008). The outside-backs covered more than twice the sprinting distance than the inside-backs, although this was not statistically significant (Roberts et al., 2008).

According to Owen (2019), a full-match analysis can provide match replacement requirements, a benchmark goal for injured players to return to play, a relative marker for training intensity, and information to help determine the "load top-ups post game" (p. 30) for players who did not play the entire match. Owen (2019) reinforces the importance of examining sub-positions in addition to the broad forwards and backs positions so that they can be trained and prepared for more accurate and relative demands in the game. They reported that while backs had significantly faster maximum speeds than the forwards, the outside backs had faster maximum speeds than the inside backs and tight forwards had lower maximum speeds than the loose forwards (Owen, 2019).

When examining the distance travelled at various speeds throughout the game, the backs are reported to cover more distance in all metrics except for jogging (2-4 $m.s^{-1}$), where the forwards were reported to cover more distance than the backs (Owen, 2019).

When sub-positional groups were examined, there was no significant difference reported between loose forwards and tight forwards, or inside backs and outside backs for total distance covered or distance covered walking (0-2 $m.s^{-1}$) (Owen, 2019). However, inside backs were reported to cover a significantly greater distance than outside backs (P = 0.03) when jogging (2-4 $m.s-^{1}$) (Owen, 2019). The tight forwards had the maximum distance covered jogging compared to the loose forwards, who had the least distance covered jogging (Owen, 2019). Tight forwards were also reported to cover a significantly lower distance striding (4-6 $m.s-^{1}$), compared to all other positions (Owen, 2019). Finally, outside backs covered a greater distance sprinting (>6 $m.s^{-1}$) than all other positions (Owen, 2019). From these findings, it is evident that not all forwards and not all backs are required to undergo similar workloads throughout a game. Therefore, future research should examine sub-positional groups, if not individual positions when quantifying match-workloads.

Eaton and George (2006) quantified the "positional demands and movement patterns of professional rugby union players competing in the English Premiership" (p. 23). They aimed to aid "position-specific rehabilitation" (p. 23), derived from "evidence based programs" (p. 23) to provide a punctual and safe return to play for the players (Eaton & George, 2006). They found that "there was no significant difference in the quantity of work to rest ratios (P=0.894) between positions" (p. 26), however, when comparing the work to rest ratio for time, a significant difference was found between positions (P<0.05) (Eaton & George, 2006). It was concluded that the outside backs had the longest recovery time, while the loose forwards had the least (Eaton & George, 2006, p. 26).

1.8 Summary

Previous literature has highlighted the importance of continually quantifying the physical demands of elite rugby players due to the game getting faster and increased player workloads. Players need to be specifically trained to meet their positional physical demands in the game, which is essential for gameplay and success during the match, as well as aiding in the prevention of injury. Future research is needed to quantify WCS in rugby union more accurately, and to identify the segment of the game that this occurs in for each positional group, which will assist coaches in preparing their players for the most intense periods of play.

It would be beneficial for future researchers to examine player demands by a rolling-play method of analysis, where the plays are not broken up, but rather examined by the number of plays that fit within a range of determined epoch lengths (5min, 10min, 15min, 20min), progressively jumping by play. Whitehead et al. (2018) had concluded that "knowledge of when the peak match demands occur, through time-stamps from the microtechnology alongside video analysis" (p. 2573) would be beneficial to coaches, posing opportunities for future research. To our knowledge, to date, there has been no research that has used a methodology which considers the true intermittent nature and irregular sequence of events in rugby to identify the stage of the game where the peak period or WCS occurs. Therefore, there is a need for future research in this area.

2 Chapter Two
Exploring and Analysing the Notion of Worst Case Scenario in Professional Rugby Union

2.1 Introduction

Rugby union is an interval-based contact sport, demanding intermittent bursts of high-intensity running, collisions and impacts. Players are often required to perform high-intensity bouts for consecutive plays, and therefore need to be conditioned for this during training (Duthie et al., 2005). Previous literature has highlighted the importance of continually updating the knowledge of the physical demands of elite rugby players due to the increase in workloads and speeds since rugby became professional in 1995 (Austin et al., 2011). Rugby consists of a series of intermittent 'plays' involving periods of 'ball in play' time (BIP) followed by periods of 'out of play' time (OOP). BIP time typically includes a series of intensive intervals involving both locomotive and contact work, and is defined as the time when the ball is in possession of a player and both teams can contest for it (Williams et al., 2005). BIP time stops when the ball goes out, or a stoppage is ordered by the referee, in which case OOP time starts and goes until the start of the next play (Williams et al., 2005). OOP time often involves light work such as repositioning (Pollard et al., 2018), or rest. The %work to rest (%W: R) is the duration of BIP time divided by the full play duration.

Understanding the maximal levels of work, defined in this study as the "worst case scenario" (WCS) in rugby union is critical to inform effective training interventions. We believe WCS is both maximal intensive workload and the maximal sustainable workload. To date, researchers examining the WCS locomotion workloads have tended to determine averages over various durations, using either a fixed-time epoch approach or a rolling-average epoch method (Cunningham et al., 2018; Delaney et al., 2017; Jones et al., 2015; Owen, 2019; Read et al., 2019; Sheppy et al., 2020). Typically, a fixed-time epoch analysis involves a series of consecutive intervals without any overlap. A rolling-average epoch analysis involves epochs of a specific duration that overlap, for example, the epoch might be 60 seconds and the start and finish times move progressively forward one second for each successive epoch. Regardless of the methodology used, the intensity of workload metrics typically decreases for all players (whole team, forwards and backs) as the epoch period being analysed increases (Cunningham et al., 2018; Reardon et al., 2017; Sheppy et al., 2020). Thus, the longer the epoch length, the lower the average work demands tend to be. Fixed-time epoch analyses have been shown to underestimate several performance metrics, and therefore underestimate the most intense periods of play. These underestimations are less likely to occur in the rolling-average analysis, previously making this the preferred methodology when quantifying WCS demands (Cunningham et al., 2018; Varley et al., 2012; Whitehead et al., 2018). The limitation of the fixed-time epoch and rolling-average methods is that the calculated workload is often an average over a timeframe, incorporating both BIP and OOP periods. Therefore the actual BIP interval work rates are likely underestimated and may not be representative of the actual workloads.

Reardon et al. (2017) defined the WCS as the longest bout of BIP time and examined the WCS differences between positional groups. They found statistically significant differences across a variety of metrics, concluding that their measure of WCS did not necessarily occur in the same play for all positions (Reardon et al., 2017). The longest play may or may not relate to the maximal workload or maximum intensities. Therefore we think it would be beneficial to explore both the longest bout of play and the greatest workloads to describe WCS.

Understanding the maximal BIP workload for each position and the maximal workloads over a series of WCS plays can help inform training interventions. We believe an effective WCS analysis should therefore examine both the maximal workload and the segment of the game this occurs in, as well as analysing maximal workloads over a series of plays fitting into various specified durations. Pollard et al. (2018) found that both the mean BIP and maximum BIP analyses returned higher metric values than the whole match average values (Pollard et al., 2018). This further demonstrates the importance of analysing shorter periods of BIP time when quantifying maximal demands as not to underestimate maximal WCS demands. The maximal workload reported over a short duration, for example, 30-60 seconds, will likely provide insights into the maximum intensity workloads required. In contrast, the maximal workload reported over a longer duration, for example, 10-20 minutes, will likely give insight into the maximal sustainable workloads required. Therefore, an effective WCS analysis needs to examine both the single highest BIP metric value and the maximal sustainable series of BIP's across various GPS metrics for each position. We define maximal sustainable workload to include the work done during the number of BIP periods that make up a series of plays that fit into specified durations. For example, rather than analysing the maximal workload over 20 minutes including both BIP and OOP work, we would look at maximal workload done only during the BIP period of a series of plays lasting ~ 20 minutes, including the time of OOP. Thus the BIP workload, duration of BIP times and the work to rest interval will help inform the maximal sustainable WCS training bout.

Owen (2019) split each half of the match evenly into 4 segments of roughly 10 minutes each to compare metrics between each segment of the game. The majority of the intense running demands occurred in the 1st segment of each half, with players generally covering a greater distance in the 1st segment compared to the 5th (Owen, 2019). It would be useful, however, to quantify the maximum demands in a broader range of metrics while identifying the segment of the game where these occur. This would give more insight into how to best prepare players, as well as help inform decisions around the ideal timing for tactical substitutions.

A common limitation among many studies, however, was that player's data who had played less than 60 minutes of the game were excluded. However, Lacome et al. (2016) suggest that substitute players often have a greater performance output when they start playing compared to those who had been playing the entire match. Therefore, substitute players have the potential to reach the maximum metric values in the game, and their data should be included when examining the maximal workload demands.

Recent WCS research we have cited, utilised global positioning systems (GPS) to quantify player workloads. While some previous studies include accelerometry data such as collisions in their analysis, we recognise the limitations with this. Currently, the ability for GPS units to quantify collision and impact activity is limited due to the tackle detection technology being unable to accurately identify types of tackles (Cummins et al., 2013). Depending on the type of collision, sometimes the acceleration signal can have large fluctuations, while other times it does not (Kelly et al., 2012), making it challenging to quantify collisions accurately. In addition to this, the GPS cannot yet quantify the intensity of work done from the slow locomotive movement that often occurs after collision and impact activities (Roe et al., 2016). Therefore, due to these limitations in current technology, we have decided to focus this study on locomotive workload demands.

This study aims to determine WCS by quantifying the maximal intensity BIP locomotive workload demands for each positional group, identifying the segment of the game they occurred in. We will also examine the maximal sustainable BIP workloads over a series of plays, including BIP and OOP time that fit into various specified epochs.

2.2 Methods

2.2.1 Participants

GPS data was collected from elite professional players from one Japanese top league club team (n=51) for 11 in-season games across the 2019-2020 seasons. Players were provided with information outlining the procedures, rationale and potential applications associated with the study. Informed consent forms were signed by team management, and all participants before the commencement of this study. The University of Waikato Human Ethics Committee granted ethical approval. Throughout this study, all participants were in full-time training and were considered to be healthy and injury-free. All players were previously familiarised with the data collection procedures, were not required to do anything outside of their regular competition and training requirements for this study. Players were grouped into the following positions: props, hooker, locks, loose forwards, halfback, first five, midfield and outside backs (age: 30yrs ± 4; Height 1.81m ± 0.08, body mass 99.67kg ± 16.87).

2.2.2 Procedures

The matches all took place between January 2019 and March 2020. All players wore GPS units (Apex Pro Pod, STATSport, Newry, NIR) which connected to the best 4 satellites and collected data at a sampling frequency of 10 Hz. Before the pre-match warm-up, GPS units were switched on and activated as per the manufacturer's guidelines ~30–60 min before kick-off. Devices were then placed in a tightly fitting, custom made pocket situated between the player's scapulae (Akenhead et al., 2014; Howe et al., 2020). These pouches are specifically designed to fit GPS units as close as possible to the athlete's body, ensure a minimal chance of accidental movement of the unit. Each player wore the same GPS unit for each match to minimise inter-unit variability (Akenhead et al., 2014; Howe et al., 2020). After the match, GPS units were switched off and gathered in a 28-point charge case which simultaneously downloaded the GPS data files for each player onto a computer.

Each match was filmed using cameras from various angles (end of the field, high cam, close cam, and side cam). After the match, these videos were synchronised (using kick-off as a matching start point) and downloaded into the Sportscode video analysis software package (Sportscode V8.9, Sportstec, Australia). The start and end time-stamps for each successive BIP period throughout each match were then created as per the rules outlined in appendix 1.

The BIP time-stamps were then exported from Sportscode and imported into the STATSports Sonra software (STATSports Sonra, Newry, NIR) where the start and finish BIP times were aligned with the GPS data. The GPS metrics chosen for analysis were based on the common locomotion metrics examined in previous WCS analysis research in rugby (Cunningham et al., 2018; Jones et al., 2015; Owen, 2019; Pollard et al., 2018; Read et al., 2019; Reardon et al., 2017; Sheppy et al., 2020). The GPS metrics chosen in this study included: distance (DISTANCE), DIST per minute (DIST/min); high speed running (HSR) and HSR per minute (HSR/min), sprint distance (SPRINT) and sprint per minute (SPRINT/min), high metabolic load distance (HMLD) and HMLD per minute (HMLD/min), and acceleration count (ACC) and ACC per minute (ACC/min). The metric zone classifications were: HSR >5.5 $m.s^{-1}$, SPRINT >7.5 $m.s^{-1}$, HMLD >25.5 w/kg and ACC >2 $m.s^{-2}$, which were calculated as per the methods used in the STATSports Sonra software (STATSports Sonra, Newry, NIR).

Separate BIP drills were then generated for each successive BIP throughout the game. This data was imported into a bespoke analysis program. Both halves of all matches were split evenly into 4 segments, overall breaking each game into 8 equal segments to show where the maximum values occurred in the game. The analysis program determined the average BIP duration as well as the longest BIP duration and which segment of the game the longest BIP occurred in. The difference between the longest BIP duration and average BIP duration were also calculated.

The maximum BIP (MaxBIP) value for each GPS metric was determined for each positional group, alongside the segment of the game that each value occurred in. The maximal sustainable workload was also determined for each GPS metric which was generated from a continuous series of combined complete plays closest to epochs of 5 (5 min), 10 (10 min), 15 (15 min) and 20 (20 min) minutes. The cut off for inclusion of these intervals was ± 1.5 of the target epoch time. This analysis was continuously repeated by moving forward one play at a time, following the same analysis procedure for each half of each game. The analysis program determined the average and longest cumulative BIP duration for each epoch plus the segments of the game the longest epochs occurred in. For each epoch, the average and maximum GPS metric values for the cumulative BIP intervals were determined for each position, along with the associated work to rest ratios and segments that they occurred in. The maximal distance and count values provided the

WCS volumes for each GPS metric. In contrast, the maximal distance per minute and count per minute values provided the WCS intensity for each GPS metric.

2.2.3 Data Analysis

Z scores were used to calculate the magnitude of difference between the maximum and mean of each metric and metric per minute. A Z score ≥ 1.96 was used to determine with a 95% confidence level that the maximum metric value was substantially larger than its mean value. Each metric per minute (DIST/min, HSR/min, SPRINT/min, ACC/min, HMLD/min) MaxBIP value was expressed as a percentage of their overall maximum for BIP, and 5, 10, 15 and 20 minute epochs to determine the differences between the maximal intensities for the MaxBIP and maximum epoch values. More in-depth visual comparisons were explored with graphs of the HMLD and HMLD/min metric. HMLD was chosen because rugby is a combination of intensive interval sprint and acceleration work and HMLD is the most effective and accurate method of representing rugby specific locomotion work (Smith et al., 2019).

2.3 Results

As shown in *Table 1.*, the %W:R ratio typically reduced as the epoch duration analysed increased. The longer epochs indicate a more maximum sustainable workload, while the shorter epochs indicate the intensity.

When comparing the whole team average results from *Table 2.* to the maximum results in *Table 3.* and *Table 4.*, it is clear that the whole team average results are far lower than the maximal results for the GPS metrics and GPS metrics per minute. This indicates that the full team averages underestimate peak performance and WCS demands. The GPS metric values presented in *Table 3.* is an indication of the maximal sustainable workloads, while the GPS metric per minute values in *Table 4.* show the maximum intensity outputs. Although the maximum GPS metric and GPS metric per minute data tended to fall in the final segments of the second half, as seen in *Figure 1., Figure 2., Figure 3., and Figure 4.*, and subsequently in *Table 3., and Table 4.*, it appears that the 5 minutes, 10 minutes and 15 minutes epoch data for HMLD tend to be higher early in the first half, as seen in *Figure 1.* It appears that the WCS BIP analysis data shown in *Table 4.* may be inaccurate, which is potentially due to the GPS accuracy limitations stated earlier.

The Z scores displayed in *Table 5.* and *Table 6.* indicate that there are large differences between the WCS and their mean values across the majority of metrics and positions. It is clear from *Figure 5., Figure 6., Figure 7., and Figure 8.* that there is no definitive pattern in the distribution of our data.

Table 1. Maximum duration and average duration values for BIP and MultiPlay WCS, the difference and Z-scores

Longest bout of BIP in:	MAXIMUM				AVERAGE			DIFFERENCE	
	Work time	Duration	%W:R	Segment	Work time	Duration	%W:R	Work time	Duration
BIP analysis	03:18	04:03	n/a	8	00:41	02:16	30%	02:37	01:47
5 minute epochs	04:28	06:16	71%	3	01:43	05:00	35%	02:45	01:16
10 minute epochs	05:36	11:13	50%	3	03:21	09:59	34%	02:15	01:14
15 minute epochs	08:45	16:30	53%	5	04:51	14:59	32%	03:54	01:31
20 minute epochs	10:05	21:24	47%	7	06:07	19:59	31%	03:58	01:25

*Table 1***.** includes the maximum duration values and average duration values for both the ball in play worst case scenario analysis, and the 5, 10, 15 and 20 minute epoch MultiPlay worst case scenario analysis. It appears that as the epoch duration increases, the work to rest ratio decreases.

Table 2. Whole team average values for GPS metrics for the BIP analysis and MultiPlay analysis.

GPS metrics and metrics/min	BIP analysis		5 minute epochs		10 minute epochs		15 minute epochs		20 minute epochs	
	Average	Stdev	Average	Stdev	Average	Stdev	Average	Stdev	Average	Stdev
DISTANCE (m)	48.6	21.8	139.6	86.7	268.3	144.2	390.8	199.6	506	251
HSR (m)	5.8	2.7	16.8	14.1	27.9	22.15	38.8	28.4	48.9	34.2
SPRINT (m)	0.9	0.8	7.2	4.8	9.7	7.2	11.7	8.9	13.6	10.3
HMLD (m)	13	7.2	40.7	27.2	77.2	45.4	111.7	61.5	142.4	76.9
ACC (count)	0.6	0.3	2.16	1.42	4	2.3	5.7	3.1	7.31	3.84
DISTANCE/min	52.3	22.8	82	40	79.9	37.6	78.7	36.3	77.8	35.5
HSR/min (m)	7.7	5.8	10.2	9.1	8.4	6.7	7.9	5.7	7.52	5.2
SPRINT/min (m)	0.8	0.7	4.4	2.9	3	2.2	2.4	1.8	2.1	1.6
HMLD/min (m)	13	7.2	24.4	15.4	23.1	12.8	22.6	11.9	21.9	11.3
ACC/min (count)	0.67	0.35	1.28	0.8	1.2	0.7	1.2	0.6	1.1	0.6

Table 2. shows the whole team average values and standard deviations for both the ball in play analysis and the MultiPlay analysis epochs.

Table 3. Maximum positional metric values for BIP WCS and MultiPlay WCS

Position	BIP analysis				5 minute epochs				10 minute epochs				15 minute epochs				20 minute epochs			
HMLD (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	77	7	01:22	n/a	156	7	02:51	58%	210	6	03:52	37%	257	7	06:39	46%	327	6	07:11	35%
Hooker	90	6	01:22	n/a	183	1	02:13	37%	295	1	03:17	30%	376	1	05:29	35%	412	2	06:31	31%
Lock	143	8	02:42	n/a	189	5	02:25	39%	279	5	04:16	39%	380	5	06:38	41%	469	7	09:03	43%
Loose	125	8	02:42	n/a	162	7	02:51	58%	239	1	04:13	39%	330	1	06:16	39%	407	5	08:36	41%
Half	179	8	02:42	n/a	247	2	02:40	46%	381	1	05:23	49%	459	3	06:34	40%	560	5	08:36	41%
First 5	159	7	03:18	n/a	206	7	02:51	58%	308	1	04:13	39%	384	6	06:20	42%	546	2	07:39	36%
Midfield	134	8	02:42	n/a	178	1	02:11	40%	269	1	05:23	49%	371	5	06:38	41%	446	3	06:50	32%
Outside	155	7	02:58	n/a	203	1	02:11	40%	314	5	04:15	40%	427	1	06:16	39%	484	1	07:23	39%
DISTANCE (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	359	8	02:42	n/a	444	8	03:44	60%	777	1	05:23	49%	925	7	06:39	46%	1233	7	09:03	43%
Hooker	275	4	03:08	n/a	455	4	04:28	71%	632	4	05:36	50%	856	1	05:29	35%	940	2	06:31	31%
Lock	351	8	02:42	n/a	430	6	03:19	60%	730	7	05:37	50%	931	5	06:50	43%	1257	7	09:03	43%
Loose	391	7	03:18	n/a	458	7	03:27	58%	678	1	05:23	49%	947	7	07:37	49%	1236	1	09:11	44%
Half	428	7	03:18	n/a	531	5	03:37	61%	951	1	05:23	49%	1125	5	06:50	43%	1454	5	08:36	41%
First 5	479	7	03:18	n/a	525	4	04:28	71%	710	7	05:06	47%	1018	7	06:41	45%	1295	5	08:47	42%
Midfield	368	8	02:42	n/a	474	8	03:44	60%	750	1	05:23	49%	910	5	06:38	41%	1092	2	07:39	36%
Outside	437	7	02:58	n/a	560	8	03:44	60%	786	1	05:23	49%	1008	1	06:16	39%	1278	7	09:03	43%
HSR (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	49	7	00:29	n/a	81	7	02:51	58%	117	6	03:52	37%	117	6	05:38	38%	122	5	08:47	42%
Hooker	57	2	00:37	n/a	129	1	01:30	27%	176	1	03:17	30%	180	1	05:29	35%	184	1	06:12	34%
Lock	101	8	02:42	n/a	123	7	01:34	33%	183	6	03:46	34%	194	5	06:38	41%	226	7	09:03	43%
Loose	96	7	00:29	n/a	96	7	00:51	14%	157	5	04:00	40%	196	1	06:21	43%	243	5	08:36	41%
Half	92	7	00:29	n/a	132	7	02:07	36%	187	5	04:00	40%	212	7	06:41	45%	278	5	08:36	41%
First 5	90	2	00:40	n/a	136	7	02:51	58%	213	3	03:18	31%	277	3	04:55	36%	313	3	06:50	32%
Midfield	100	4	01:58	n/a	134	5	02:25	39%	188	8	04:52	44%	255	5	06:38	41%	274	7	06:44	33%
Outside	115	4	01:58	n/a	170	5	01:57	47%	275	6	04:06	42%	359	1	06:16	39%	394	1	07:23	39%
SPRINT (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	12	7	01:22	n/a	13	7	02:51	58%	13	6	03:52	37%	13	6	05:38	38%	13	5	08:47	42%
Hooker	29	3	01:44	n/a	35	5	01:27	24%	47	5	02:53	26%	48	5	04:16	28%	48	5	05:24	26%
Lock	49	8	02:42	n/a	59	7	01:34	33%	68	7	04:51	46%	81	7	05:32	38%	81	2	07:49	40%
Loose	42	7	00:29	n/a	58	5	02:18	47%	88	5	04:00	40%	94	1	06:21	43%	94	1	09:11	44%
Half	60	7	00:30	n/a	73	7	01:34	33%	76	6	03:16	32%	78	7	05:32	38%	79	2	07:49	40%
First 5	60	2	00:40	n/a	66	2	01:36	30%	66	1	04:13	39%	76	1	05:23	38%	86	1	07:36	36%
Midfield	54	8	00:48	n/a	54	8	01:08	23%	74	8	04:52	44%	94	5	05:38	36%	121	5	07:35	38%
Outside	81	4	01:58	n/a	95	5	01:57	47%	168	5	04:15	40%	168	5	06:23	43%	173	2	07:39	36%
ACC (count)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	8	8	02:19	n/a	9	8	03:42	60%	12	8	04:34	43%	16	2	06:12	38%	21	7	08:43	43%
Hooker	8	7	02:26	n/a	8	2	01:42	30%	15	6	03:37	32%	19	2	04:45	31%	21	1	06:12	34%
Lock	8	7	03:18	n/a	11	1	02:00	47%	19	1	04:44	44%	24	2	05:18	36%	30	2	07:39	36%
Loose	7	7	02:09	n/a	9	8	03:42	60%	16	5	05:23	55%	20	5	06:51	50%	27	5	09:11	44%
Half	9	6	02:32	n/a	14	5	02:42	47%	19	5	03:45	34%	26	5	05:44	37%	31	5	06:57	33%
First 5	6	2	01:37	n/a	11	6	02:48	45%	17	3	05:23	48%	22	1	06:55	43%	28	2	07:39	36%
Midfield	7	5	02:43	n/a	10	6	02:54	48%	17	5	03:51	38%	21	1	05:18	33%	26	2	06:36	31%
Outside	6	7	01:14	n/a	11	6	02:54	48%	16	2	04:00	42%	22	1	06:16	39%	26	2	07:16	36%

Table 3. shows the maximum ball in play values for each position and each metric. Values are presented for both the ball in play analysis and the MultiPlay analysis epochs. The corresponding segments are shown for where each maximum metric value occurred during the respective game. The duration of the BIP time and work to rest ratios are also expressed.

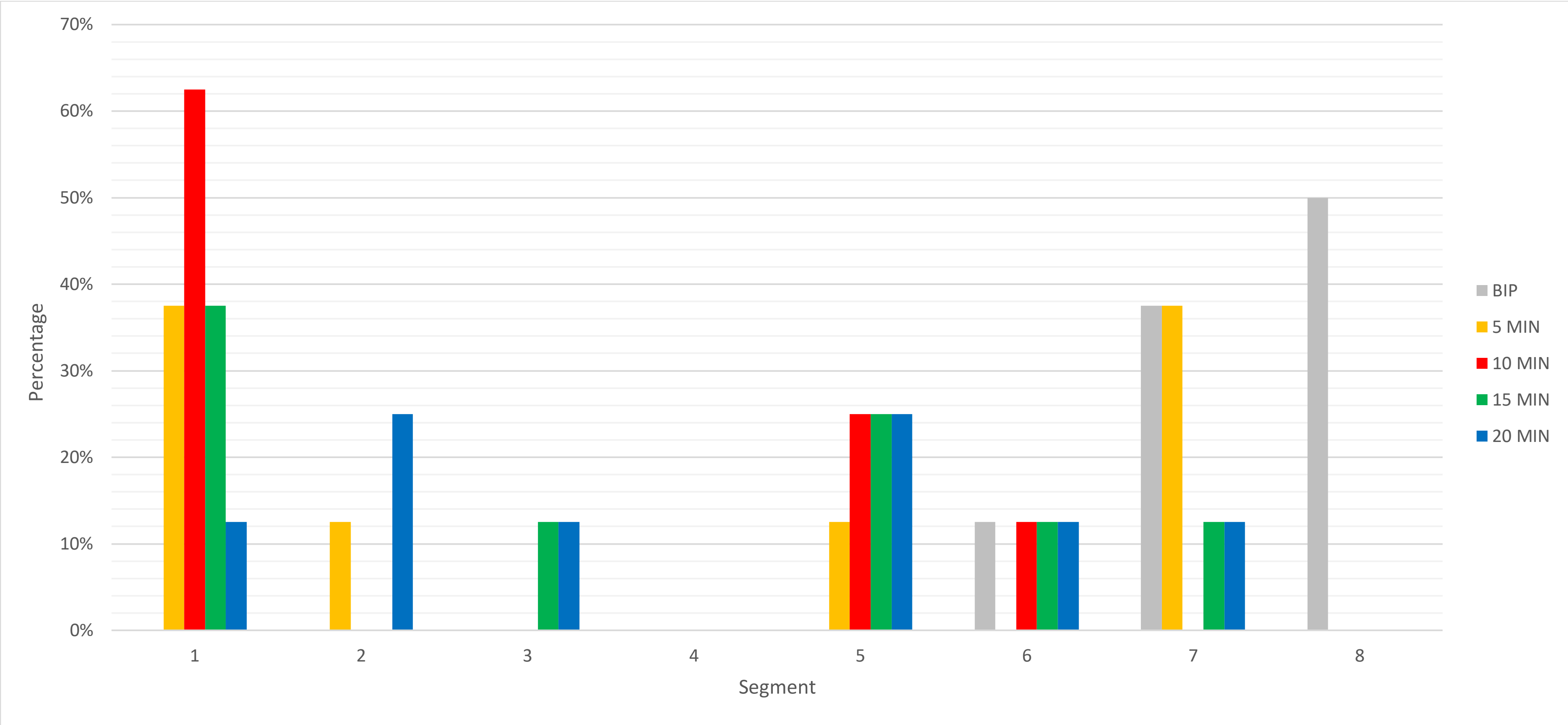

Figure 1. Segments where cumulative positions maximum HMLD occurred for BIP and MultiPlay epochs (percentage)

Figure 1. shows the segments where the maximum high metabolic load distance occurred for ball in play and MultiPlay epochs for cumulative positions. There is no clear pattern here.

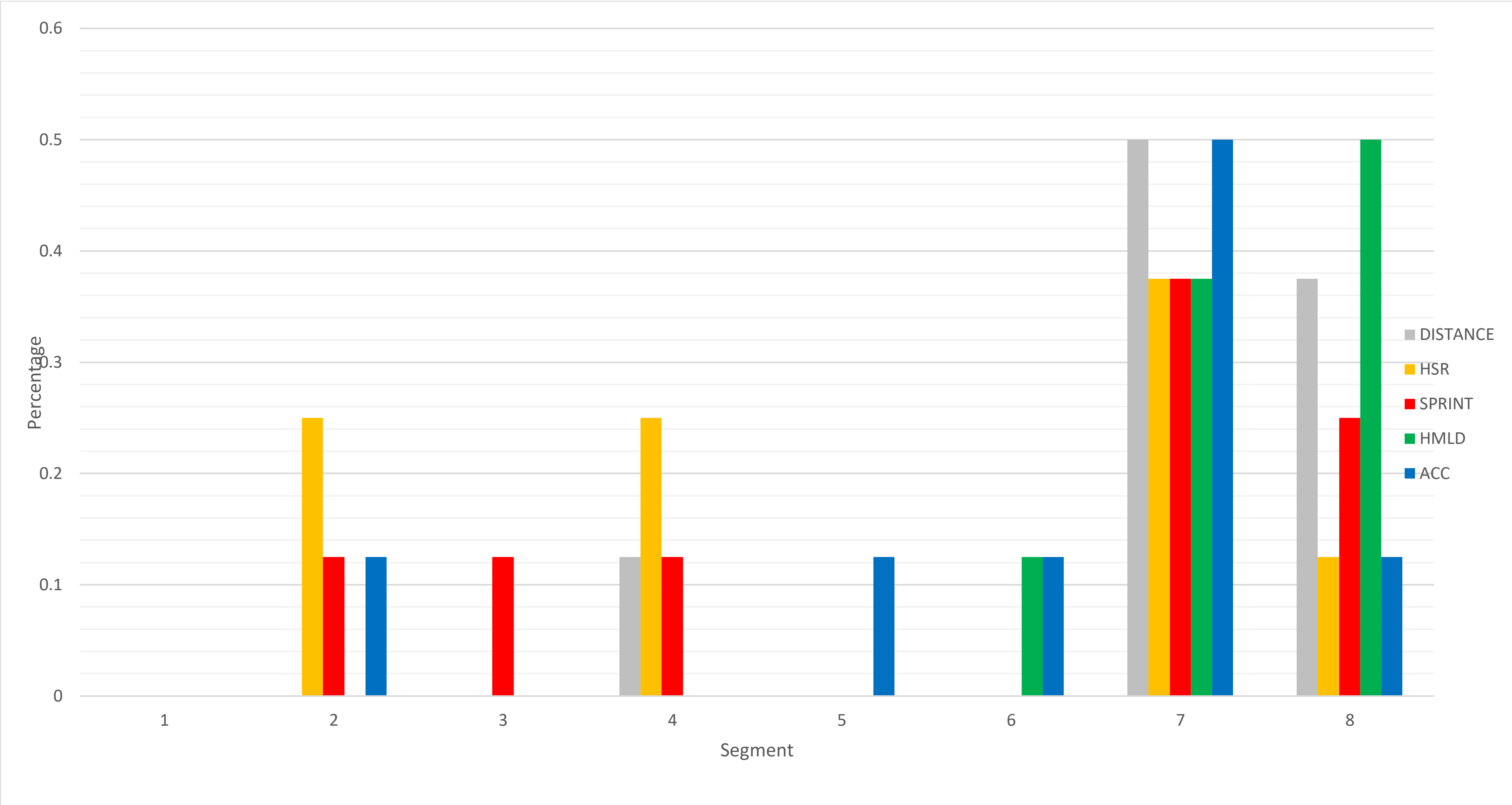

Figure 2. Segments where cumulative positions maximum metric values occurred during BIP (percentage)

Figure 2**.** shows that segments 7 and 8 are where majority of the maximum metric values occurred for all positions combined.

Table 4 Maximum positional metric/min values for BIP WCS and MultiPlay WCS

Position	BIP analysis				5 minute epochs				10 minute epochs				15 minute epochs				20 minute epochs			
HMLD/min (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	170.0	8	00:47	n/a	91.2	7	00:25	13%	65.4	7	01:52	20%	58.6	6	03:27	24%	56.1	6	04:07	20%
Hooker	166.0	4	00:25	n/a	121.1	2	00:56	25%	89.8	1	03:17	30%	74.1	1	04:36	31%	68.1	1	05:39	27%
Lock	217.0	1	00:21	n/a	140.0	7	00:51	14%	80.0	4	02:30	26%	65.9	6	04:14	26%	57.2	7	06:20	30%
Loose	333.0	8	00:21	n/a	143.5	7	00:51	14%	85.5	7	01:46	20%	73.1	5	03:45	25%	69.1	5	03:58	22%
Half	307.0	8	00:21	n/a	131.7	3	00:41	15%	92.6	7	02:51	29%	85.3	1	04:14	29%	77.0	1	05:39	31%
First 5	332.0	8	00:22	n/a	117.8	4	00:55	18%	84.8	4	02:30	26%	82.6	3	04:34	31%	75.0	2	06:51	36%
Midfield	320.0	8	00:21	n/a	132.0	7	00:25	13%	86.0	7	01:46	20%	78.9	5	01:45	13%	69.1	3	06:09	33%
Outside	295.0	8	00:29	n/a	136.4	4	00:55	18%	93.8	1	03:17	30%	80.7	1	04:36	31%	73.7	7	06:20	30%
DIST/min (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	1115.4	7	00:20	n/a	242.4	7	00:51	14%	166.1	7	01:52	20%	155.7	6	04:14	26%	147.2	5	03:58	22%
Hooker	861.7	4	00:32	n/a	223.9	2	00:56	25%	177.3	1	03:17	30%	160.0	1	04:36	31%	151.5	1	05:39	27%
Lock	1098.9	7	00:20	n/a	237.6	7	00:51	14%	162.0	4	02:30	26%	150.9	7	04:40	31%	149.5	7	06:20	30%
Loose	1290.3	7	00:20	n/a	210.6	7	00:51	14%	169.8	7	01:46	20%	160.8	5	03:45	25%	153.8	5	03:58	22%
Half	1412.4	7	00:20	n/a	229.1	8	01:28	33%	198.6	3	02:12	23%	186.5	3	03:13	20%	175.4	7	06:20	30%
First 5	1580.7	7	00:20	n/a	205.1	4	00:55	18%	176.4	4	02:30	26%	168.6	3	04:34	31%	160.7	7	06:20	30%
Midfield	1138.5	7	00:20	n/a	204.0	7	00:25	13%	162.6	3	02:52	28%	159.3	2	03:58	26%	152.4	7	06:20	30%
Outside	1296.4	7	00:29	n/a	225.0	2	00:56	25%	187.6	1	03:17	30%	173.3	1	04:36	31%	162.3	7	06:29	34%
HSR/min (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	164.0	5	00:13	n/a	58.0	5	01:00	28%	39.1	5	01:29	19%	33.1	5	01:45	13%	24.3	6	04:07	20%
Hooker	302.0	3	00:22	n/a	94.3	2	00:56	25%	53.6	1	03:17	30%	38.9	1	04:36	31%	32.4	1	05:39	27%
Lock	213.0	6	00:22	n/a	115.3	7	00:51	14%	55.5	6	03:08	34%	44.6	6	04:06	29%	31.0	5	06:21	31%
Loose	225.0	3	00:32	n/a	112.9	7	00:51	14%	58.3	7	01:46	20%	45.8	6	03:27	24%	38.4	6	04:07	20%
Half	267.0	5	00:22	n/a	121.1	4	00:55	18%	60.7	4	02:41	27%	43.5	3	02:36	20%	35.2	1	05:39	31%
First 5	260.0	7	00:35	n/a	124.4	4	00:55	18%	66.3	4	02:41	27%	56.3	3	04:55	36%	48.6	3	06:09	33%
Midfield	203.0	5	00:46	n/a	112.8	7	00:25	13%	57.6	4	02:28	26%	57.1	5	01:45	13%	42.3	7	06:29	34%
Outside	301.0	6	00:32	n/a	117.8	4	00:55	18%	78.3	5	03:10	36%	63.2	2	05:19	35%	57.5	4	06:18	34%
SPRINT/min (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	16.4	7	00:47	n/a	8.8	7	01:22	48%	3.9	7	03:21	41%	3.0	7	04:16	34%	2.0	6	06:25	34%
Hooker	11.9	2	00:37	n/a	26.7	5	01:03	27%	17.6	5	02:40	27%	12.4	5	03:48	24%	10.8	5	04:21	23%
Lock	132.3	8	00:21	n/a	37.7	7	01:34	33%	20.9	7	02:49	28%	14.6	7	05:32	38%	11.2	6	06:03	31%
Loose	49.2	4	01:35	n/a	49.4	7	00:51	14%	25.4	5	03:28	38%	17.3	2	05:06	34%	11.3	2	07:49	40%
Half	44.2	8	01:55	n/a	60.0	7	00:51	14%	25.9	7	02:49	28%	18.5	6	04:06	29%	12.5	6	06:04	31%
First 5	59.4	8	00:45	n/a	41.3	2	01:36	30%	20.4	2	03:14	32%	14.1	1	04:40	31%	11.3	1	07:36	36%
Midfield	97.2	8	00:21	n/a	47.6	8	01:08	23%	25.7	8	02:41	34%	16.7	5	05:38	36%	16.0	5	07:35	38%
Outside	159.3	4	01:35	n/a	49.1	4	00:55	18%	41.4	5	03:10	36%	26.3	5	06:23	43%	22.8	2	04:28	23%
ACC/min (m)	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio	Value	Segment	Duration	W:R ratio
Prop	19.8	7	00:22	n/a	5.4	2	00:54	25%	4.1	6	01:42	19%	3.3	6	03:03	21%	3.4	6	04:07	20%
Hooker	12.5	4	00:33	n/a	5.8	2	01:00	31%	4.5	8	02:27	29%	4.1	4	04:08	30%	3.4	1	06:12	34%
Lock	26.4	7	00:22	n/a	6.7	1	01:42	28%	4.6	2	02:51	27%	4.5	2	05:18	36%	4.1	2	06:09	29%
Loose	23.1	7	00:22	n/a	7.2	7	00:24	13%	5.1	7	01:46	20%	4.1	6	03:27	24%	3.9	6	04:07	20%
Half	22.8	6	00:31	n/a	5.8	5	01:54	33%	5.4	5	03:09	36%	4.6	5	04:59	31%	4.5	5	06:43	32%
First 5	16.5	7	00:22	n/a	5.2	2	01:36	39%	4.8	2	03:20	31%	4.4	2	05:02	32%	4.1	2	06:16	30%
Midfield	23.1	7	00:22	n/a	6.7	3	01:12	28%	4.8	7	01:52	20%	4.3	1	04:14	29%	4.0	2	06:16	30%
Outside	16.5	7	00:22	n/a	6.7	6	00:30	14%	5.2	6	01:09	13%	4.8	6	01:27	10%	3.9	1	05:39	27%

Table 4. shows the maximum ball in play values for each position and each metric per minute. Values are presented for both the ball in play analysis and the MultiPlay analysis epochs. The corresponding segments are shown for where each maximum metric per minute value occurred during the respective game. The duration of the BIP time and work to rest ratios are also expressed.

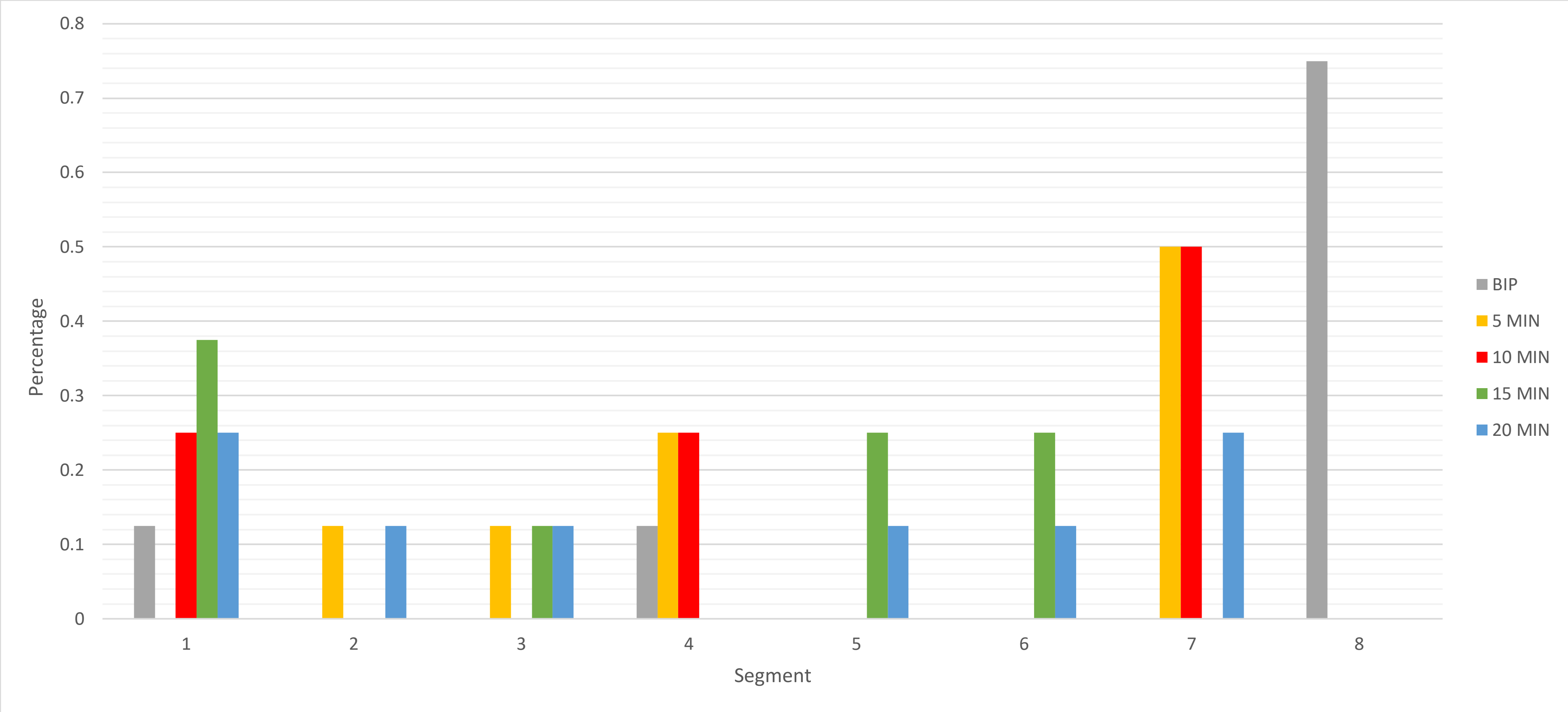

Figure 3. Segments where cumulative positions maximum HMLD/min occurred (percentage)

Figure 3. shows the segments where the maximum high metabolic load distance per minute occurred for ball in play and MultiPlay epochs for cumulative positions. It appears that segment 8 is where the maximum HMLD occurred for any single bout of BIP time for the majority of positions, however there are no other clear patterns.

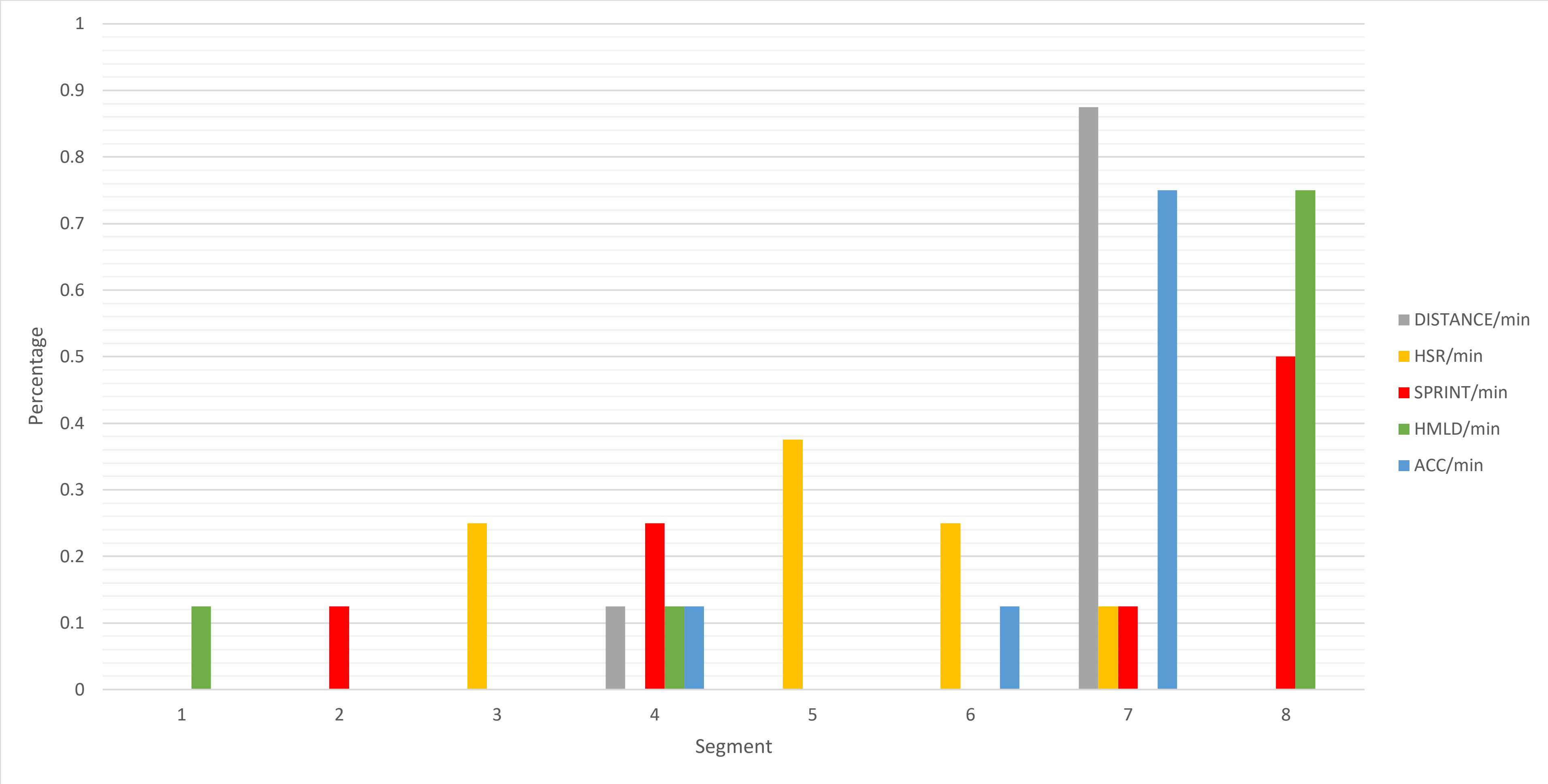

Figure 4. Segments where each BIP maximum metric/minute occurred for cumulative positions (percentage)

Figure 4. shows the segments where the ball in play maximum metric per minute values occurred for all positions combined. It appears that segments 7 has a stronger dominance than all other segments for distance per minute and acceleration count per minute, while segment 8 shows a stronger dominance for high metabolic load distance per minute. There are no other clear patterns.

Table 5. Averages and Z scores for each metric and position, for BIP and MultiPlay

Analysis	Position	Average DISTANCE (m)			Average HSR (m)			Average SPRINT (m)			Average HMLD (m)			Average ACC (count)		
		Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score
BIP	Prop	60.8	51.5	18.6	4.8	3.6	16.3	1.1	0.3	55.1	11.6	10.0	37.8	0.9	0.8	21.5
	Hooker	88.0	65.5	11.8	12.8	7.6	11.2	7.1	2.0	14.2	27.4	18.2	9.8	2.0	1.2	14.3
	Lock	96.3	75.3	11.3	9.7	10.2	25.8	8.2	3.6	34.7	22.5	20.5	18.1	1.6	1.3	11.5
	Loose	83.3	66.0	16.0	10.4	10.5	16.5	5.7	4.0	14.3	22.4	17.9	38.5	1.4	1.1	14.9
	Half	87.6	67.8	4.9	15.1	13.1	8.4	8.0	4.7	11.3	33.5	25.5	17.0	1.4	1.0	8.5
	First 5	94.5	74.7	4.0	16.2	14.1	5.9	9.8	5.4	9.3	33.0	25.8	20.5	1.8	1.4	5.1
	Midfield	90.3	74.8	12.1	15.1	14.2	12.8	8.1	5.3	16.7	27.6	24.1	23.7	1.6	1.3	11.2
	Outside	108.3	81.0	14.7	19.5	19.1	10.8	9.1	7.9	19.0	35.3	29.0	31.3	1.7	1.2	11.7
5 minutes	Prop	82.6	50.5	7.1	4.5	4.1	18.6	0.8	0.2	52.3	14.8	11.1	12.7	1.1	0.8	10.3
	Hooker	151.9	94.0	3.2	19.2	13.1	8.4	10.7	3.6	6.7	46.7	28.3	4.8	3.2	1.8	2.7
	Lock	157.6	91.3	3.0	10.5	10.1	11.1	6.2	2.9	18.3	34.6	24.2	6.4	2.2	1.5	5.9
	Loose	122.2	73.3	4.6	11.2	11.1	7.6	4.7	4.7	11.4	31.0	20.5	6.4	1.8	1.1	6.4
	Half	141.6	106.7	3.6	21.8	18.3	6.0	8.8	6.1	10.5	53.7	38.3	5.0	2.0	1.5	8.1
	First 5	150.9	108.5	3.4	22.5	19.4	5.9	10.4	7.3	7.6	51.5	36.5	4.2	2.6	1.9	4.5
	Midfield	139.4	86.5	3.9	18.6	16.3	7.1	7.2	5.4	8.7	41.3	28.7	4.8	2.2	1.6	4.8
	Outside	170.8	82.9	4.7	25.7	20.7	7.0	9.0	7.9	10.9	52.3	30.2	5.0	2.3	1.2	7.1
10 minutes	Prop	161.3	77.3	8.0	6.0	6.1	18.3	1.0	0.3	35.3	28.1	17.3	10.5	1.8	1.1	9.1
	Hooker	290.4	176.3	1.9	23.5	19.3	7.9	5.3	6.0	5.2	84.6	51.0	4.1	6.0	3.3	2.8
	Lock	308.8	154.0	2.7	18.4	18.4	9.0	8.4	5.0	12.0	68.6	43.0	4.9	4.0	2.5	5.9
	Loose	237.3	116.5	3.8	19.1	18.4	7.5	6.4	7.7	10.7	59.7	34.3	5.2	3.4	1.7	7.4
	Half	253.8	181.2	3.8	38.9	28.2	5.3	10.6	8.9	7.3	98.6	63.9	4.4	3.6	2.4	6.4
	First 5	285.8	186.3	2.3	37.4	29.2	6.0	12.2	10.3	5.2	96.4	60.5	3.5	4.7	3.1	4.0
	Midfield	273.2	144.3	3.3	31.9	25.3	6.2	9.4	7.5	8.6	79.1	47.5	4.0	3.9	2.6	5.1
	Outside	335.4	117.6	3.8	48.5	32.5	7.0	14.0	12.3	12.6	102.5	45.2	4.7	4.4	1.8	6.5
15 minutes	Prop	240.9	103.9	6.6	7.7	7.5	14.6	1.0	0.4	30.2	41.6	22.9	9.4	2.6	1.5	9.0
	Hooker	405.2	251.3	1.8	30.9	23.6	6.3	16.4	7.3	4.3	116.8	71.5	3.6	8.3	4.7	2.3
	Lock	457.2	216.8	2.2	24.8	24.8	6.8	11.7	6.6	10.5	101.6	60.3	4.6	5.6	3.3	5.5
	Loose	352.4	161.2	3.7	26.7	23.1	7.3	7.1	9.0	9.6	87.9	46.3	5.2	5.0	2.2	6.9
	Half	359.0	256.0	3.0	53.9	37.5	4.2	12.7	11.0	5.9	140.7	88.3	3.6	5.0	3.2	6.6
	First 5	405.7	261.7	2.3	51.0	36.5	6.2	14.1	12.1	5.1	136.4	82.5	3.0	6.8	4.2	3.6
	Midfield	407.9	202.5	2.5	45.3	34.4	6.1	11.9	9.6	8.6	116.9	66.1	3.8	5.8	3.6	4.3
	Outside	498.5	143.1	3.6	69.9	39.5	7.3	18.6	14.8	10.1	151.7	54.1	5.1	6.5	2.2	6.9
20 minutes	Prop	315.0	128.9	7.1	9.4	9.1	12.4	1.0	0.5	25.6	54.8	28.6	9.5	3.4	1.9	9.3
	Hooker	531.0	320.6	1.3	37.4	27.0	5.4	17.9	8.3	3.6	143.2	90.1	3.0	10.1	5.9	1.8
	Lock	593.5	276.4	2.4	29.9	30.5	6.4	13.9	7.8	8.6	132.0	76.5	4.4	7.1	4.1	5.6
	Loose	462.8	203.8	3.8	34.8	28.0	7.4	8.2	10.1	8.5	115.8	58.4	5.0	6.6	2.7	7.5
	Half	455.0	328.2	3.0	65.0	44.6	4.8	14.3	12.6	5.1	172.7	110.2	3.5	6.4	3.9	6.3
	First 5	515.9	330.7	2.4	65.3	44.8	5.5	16.1	13.9	5.0	173.0	105.1	3.5	8.9	5.2	3.7
	Midfield	524.2	251.7	2.3	57.2	41.2	5.3	14.2	11.5	9.3	149.9	82.0	3.6	7.5	4.4	4.2
	Outside	650.6	168.6	3.7	91.7	48.2	6.3	23.4	17.5	8.5	197.9	64.2	4.5	8.4	2.5	6.9

*Table 5***.** shows the average values, standard deviations and Z scores for all positions across all metrics for the ball in play analysis and the MultiPlay epoch analysis.

Table 6. Averages and Z scores for each metric/min and position, for BIP and MultiPlay

Analysis	Position	Average DISTANCE/min			Average HSR/min			Average SPRINT/min			Average HMLD/min			Average ACC/min		
		Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score	Average	Stdev	Z Score
BIP	Prop	55.6	25.9	11.7	5.2	4.3	23.1	0.9	0.2	47.8	11.1	8.8	15.1	0.8	0.5	13.1
	Hooker	82.8	48.1	4.0	12.6	7.7	11.1	7.1	2.0	15.6	26.9	15.6	6.0	1.9	0.9	6.6
	Lock	88.9	43.3	6.0	9.1	9.6	12.9	7.7	3.4	17.3	21.3	15.5	8.9	1.4	0.9	7.7
	Loose	76.4	31.9	9.6	10.1	10.5	12.7	5.7	4.8	16.0	21.3	14.0	10.7	1.3	0.8	9.9
	Half	85.1	55.1	3.3	15.0	13.3	10.8	8.1	4.8	23.1	33.0	23.2	7.4	1.4	0.9	6.9
	First 5	91.1	52.3	2.5	15.0	13.5	8.9	9.1	5.6	14.5	31.4	21.3	5.9	1.6	1.1	4.6
	Midfield	83.1	40.2	7.1	13.7	12.1	9.4	7.7	5.6	17.5	25.8	17.2	7.1	1.5	0.9	6.4
	Outside	99.3	32.7	10.3	18.0	16.0	7.9	8.2	7.0	11.2	32.8	18.1	6.7	1.5	0.8	7.5
5 minutes	Prop	48.3	22.2	8.7	3.0	3.0	18.3	0.5	0.1	59.1	8.9	7.1	11.6	0.6	0.4	11.7
	Hooker	94.0	54.4	2.4	12.2	8.8	9.4	6.9	2.4	8.1	29.6	17.7	5.2	2.0	1.1	3.4
	Lock	93.0	43.9	3.3	6.6	7.5	14.5	3.5	1.8	18.6	20.9	14.0	8.5	1.2	0.8	7.1
	Loose	71.1	31.3	4.5	7.0	7.4	14.3	2.9	3.0	15.5	18.6	12.0	10.4	1.1	0.6	9.9
	Half	81.2	53.6	2.8	13.0	11.2	9.6	5.4	3.6	15.0	31.5	20.8	4.8	1.2	0.8	5.8
	First 5	87.2	50.2	2.3	13.0	11.2	10.0	5.9	4.0	8.7	30.0	18.7	4.7	1.5	0.9	3.9
	Midfield	82.1	40.4	3.0	11.4	10.5	9.6	4.5	3.7	11.8	24.9	16.9	6.3	1.3	0.9	5.8
	Outside	99.7	27.2	4.6	15.4	13.0	7.9	5.3	4.8	9.2	31.1	15.6	6.7	1.4	0.7	7.9
10 minutes	Prop	48.1	19.2	6.1	1.9	2.0	18.7	0.3	0.1	36.9	8.5	5.2	10.9	0.5	0.3	10.9
	Hooker	88.2	52.2	1.7	7.4	6.2	7.5	5.3	2.0	6.0	26.0	15.6	4.1	1.8	1.0	2.7
	Lock	92.5	41.3	1.7	5.4	5.4	9.3	2.4	1.4	13.2	20.5	11.9	5.0	1.2	0.7	5.1
	Loose	70.5	28.9	3.4	5.8	5.5	9.6	1.9	2.2	10.6	17.9	9.7	7.0	1.0	0.5	8.4
	Half	75.0	50.9	2.4	11.8	8.7	5.7	3.2	2.7	8.5	29.3	18.5	3.4	1.1	0.7	6.1
	First 5	83.5	48.1	1.9	11.0	8.5	6.5	3.6	3.0	5.6	28.2	16.3	3.5	1.4	0.8	4.2
	Midfield	81.9	37.9	2.1	9.7	7.6	6.3	3.0	2.4	9.6	23.9	13.6	4.6	1.2	0.8	4.8
	Outside	99.3	22.3	4.0	14.5	9.6	6.6	4.1	3.5	10.5	30.5	11.7	5.4	1.3	0.5	7.8
15 minutes	Prop	48.4	17.6	6.1	1.6	1.7	18.4	0.2	0.1	38.0	8.5	4.6	10.9	0.5	0.3	9.3
	Hooker	83.6	51.5	1.5	6.7	5.2	6.1	3.8	1.7	5.0	24.5	15.1	3.3	1.7	1.0	2.4
	Lock	93.0	40.7	1.4	4.9	4.8	8.4	2.2	1.3	10.0	20.6	11.4	4.0	1.1	0.6	5.5
	Loose	70.7	27.9	3.2	5.4	4.5	9.1	1.4	1.6	9.8	17.8	8.7	6.4	1.0	0.4	7.1
	Half	71.3	50.0	2.3	10.7	7.5	4.4	2.5	2.2	7.2	27.9	17.3	3.3	1.0	0.6	5.6
	First 5	80.1	46.4	1.9	10.2	7.0	6.6	2.8	2.5	4.6	27.1	15.2	3.7	1.4	0.8	3.9
	Midfield	82.4	37.2	2.1	9.3	7.1	6.8	2.5	2.0	7.2	23.9	13.3	4.1	1.2	0.7	4.3
	Outside	100.1	19.0	3.9	14.1	7.7	6.4	3.7	2.8	8.1	30.5	9.3	5.4	1.3	0.4	7.8
20 minutes	Prop	48.3	16.9	5.8	1.5	1.5	15.2	0.2	0.1	28.8	8.4	4.3	11.2	0.5	0.3	10.1
	Hooker	83.4	50.2	1.4	6.3	4.8	5.5	3.3	1.6	4.8	22.9	14.6	3.1	1.6	0.9	1.9
	Lock	91.9	39.7	1.5	4.4	4.3	6.1	2.0	1.1	8.4	20.3	10.9	3.4	1.1	0.6	5.1
	Loose	70.7	27.3	3.0	5.3	3.9	8.4	1.2	1.3	7.7	17.8	8.2	6.3	1.0	0.4	7.2
	Half	68.7	49.0	2.2	9.8	6.7	3.8	2.1	1.9	5.5	26.0	16.5	3.1	1.0	0.6	5.6
	First 5	78.0	46.1	1.8	9.9	6.6	5.9	2.4	2.1	4.1	26.2	14.9	3.3	1.3	0.7	3.7
	Midfield	81.1	36.2	2.0	8.9	6.4	5.2	2.2	1.8	7.8	23.3	12.5	3.7	1.2	0.7	4.1
	Outside	99.9	18.1	3.4	14.1	7.0	6.2	3.6	2.5	7.6	30.4	8.4	5.1	1.3	0.4	6.5

*Table 6***.** shows the average values, standard deviations and Z scores for all positions across all metrics per minute for the ball in play analysis and the MultiPlay epoch analysis.

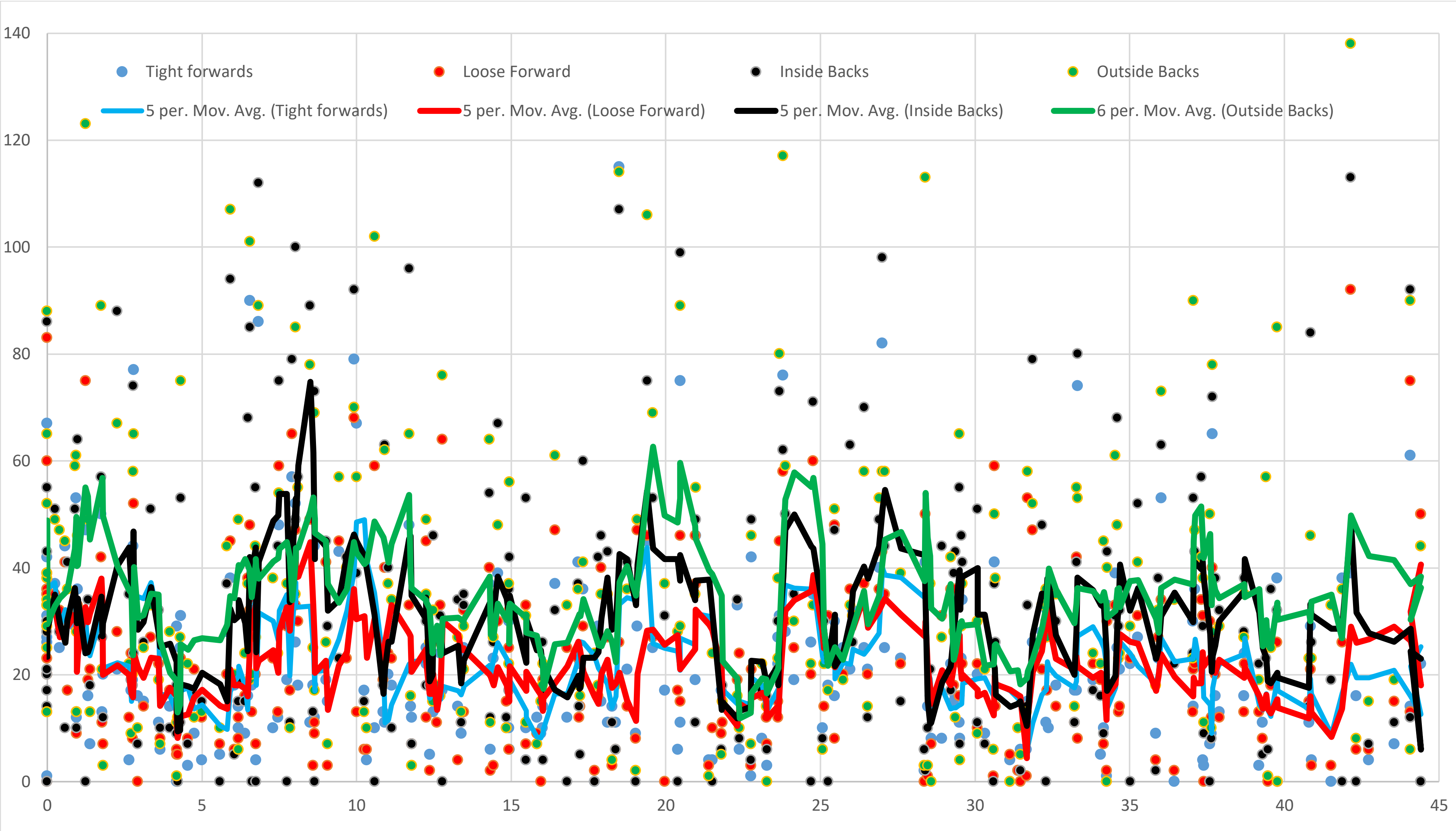

Figure 5. HMLD maximum values for BIP by position for the 1st half

Figure 5. shows a distribution graph of maximum high metabolic load distances during ball in play time for each position in the 1st half. There are no clear patterns.

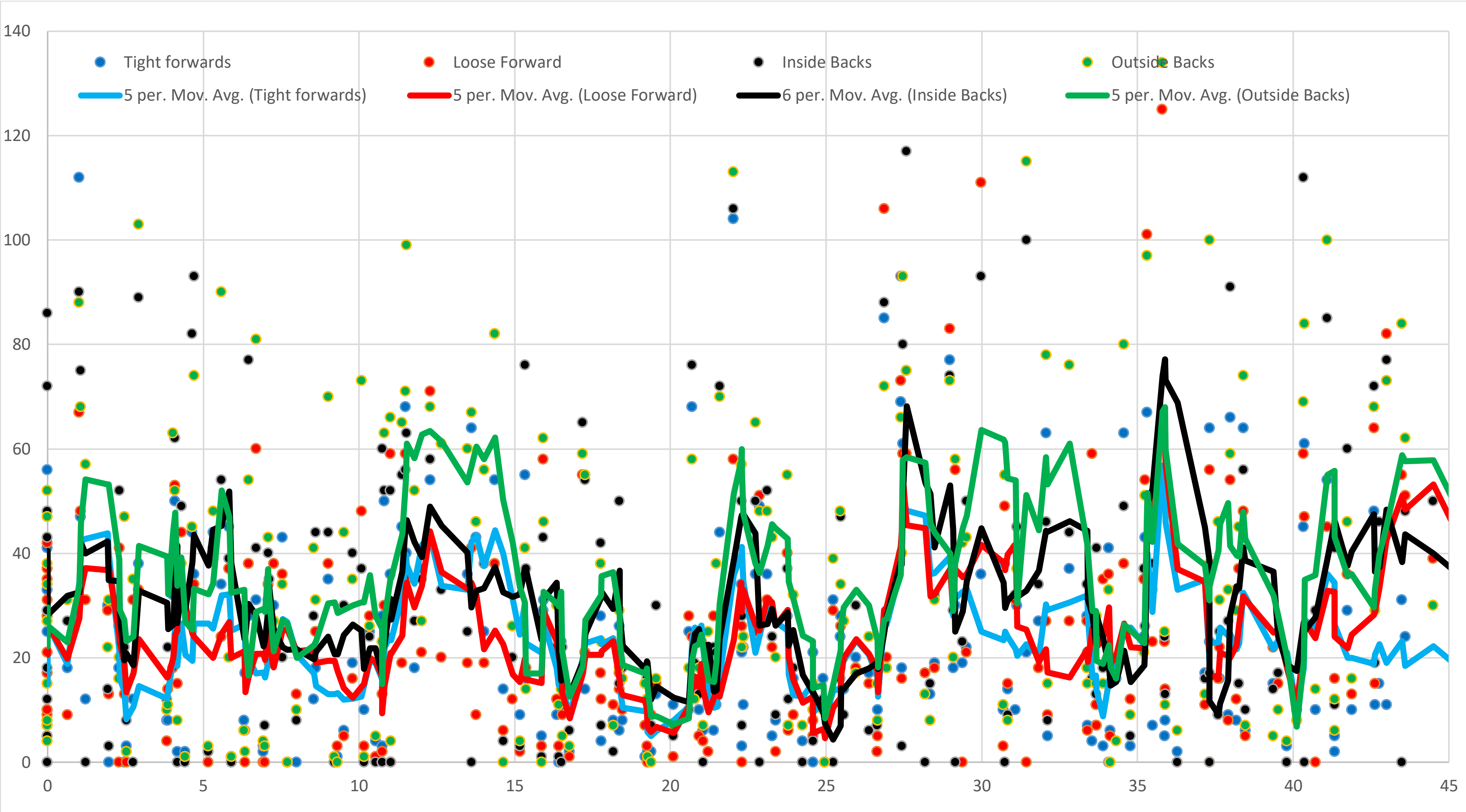

Figure 6. HMLD maximum values for BIP by position for the 2nd half

Figure 6. shows a distribution graph of maximum high metabolic load distances during ball in play time for each position in the 2nd half. There are no clear patterns.

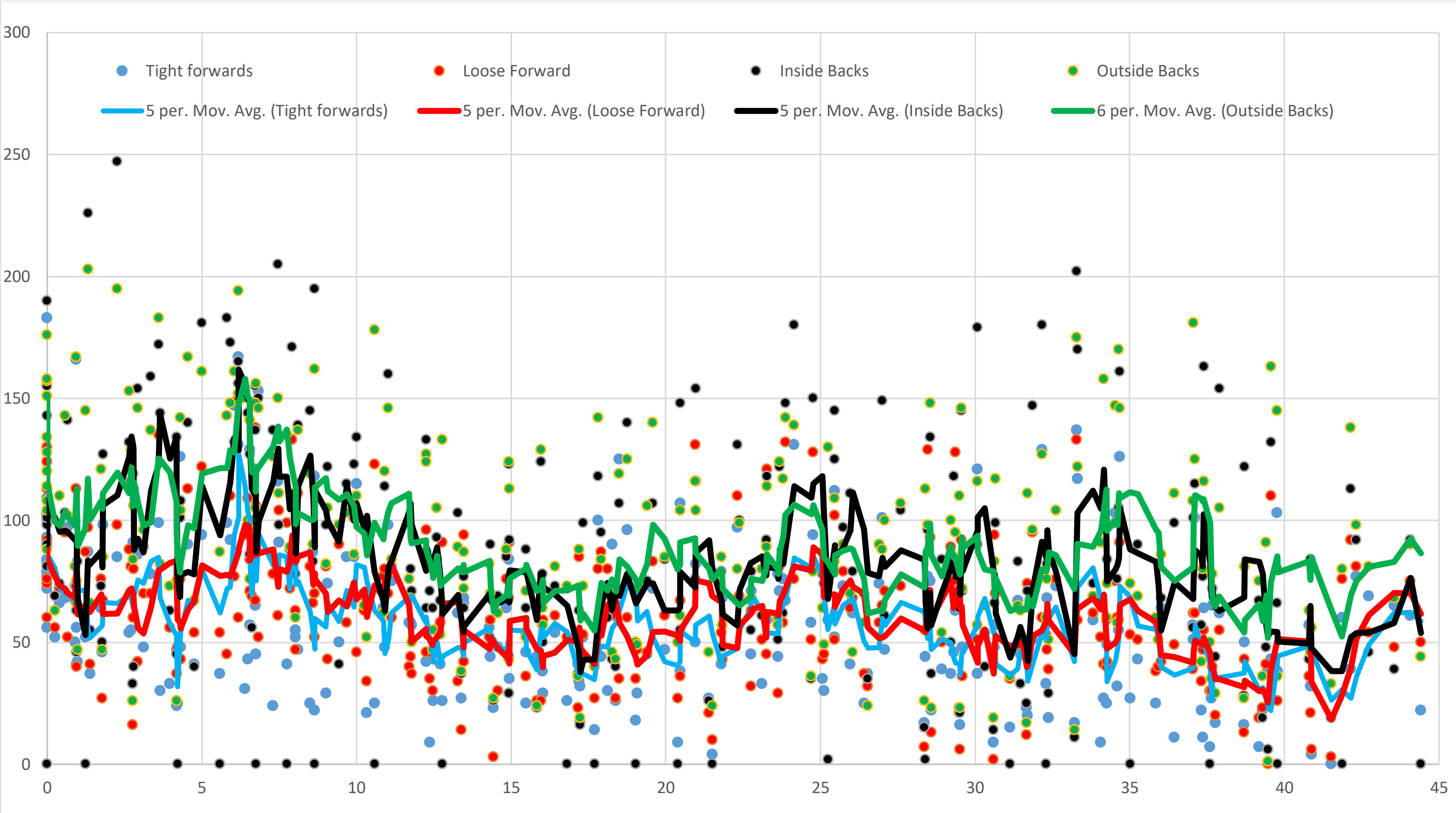

Figure 7. HMLD maximum values for 5 minute epoch by position 1st half

Figure 7. shows a distribution graph of maximum high metabolic load distances throughout 5 minute epochs for each position in the 1st half. There are no clear patterns.

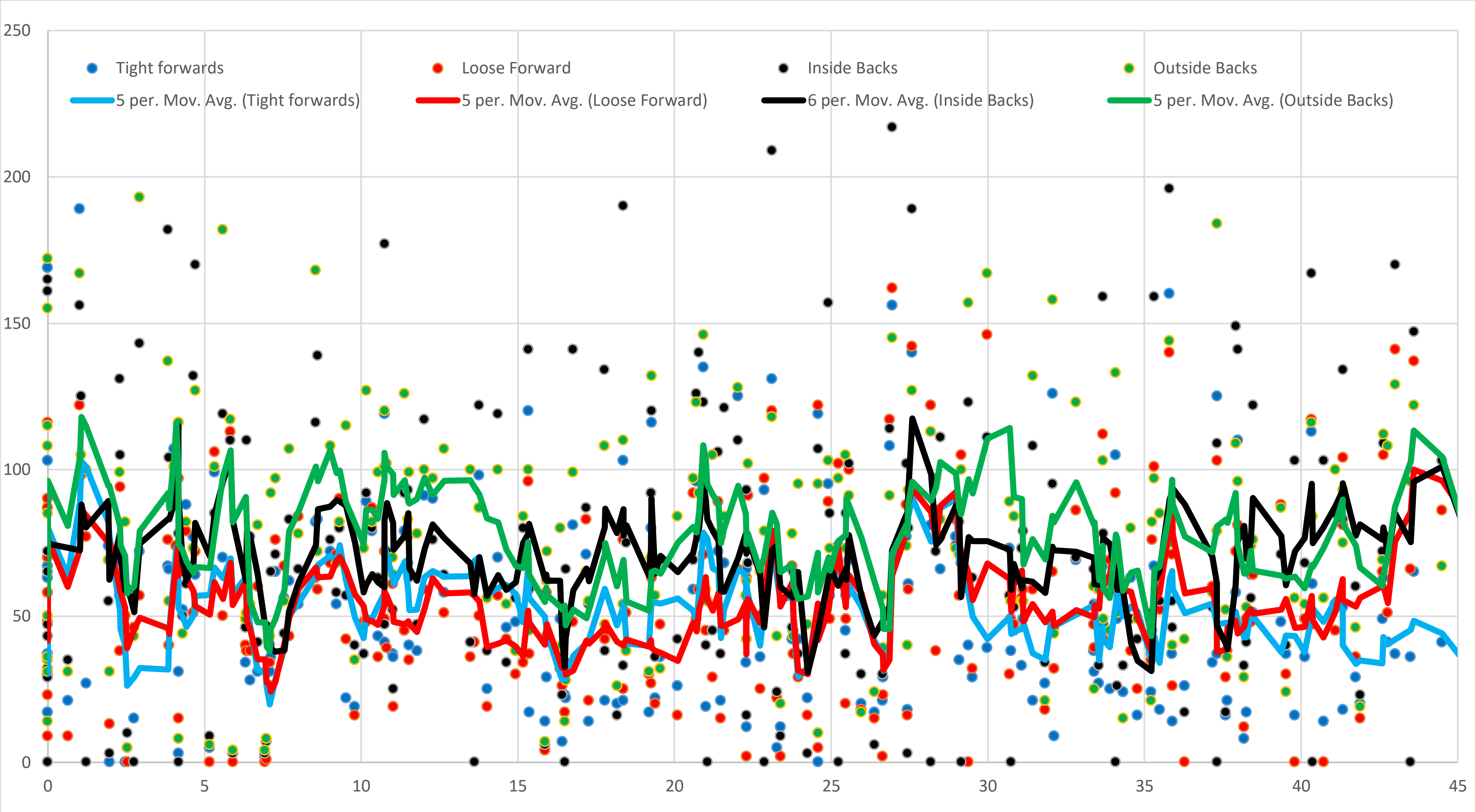

Figure 8. HMLD maximum values for 5 minute epoch by position 2nd half

Figure 8. shows a distribution graph of maximum high metabolic load distances throughout 5 minute epochs for each position in the 2nd half.

2.4 Discussion

Fundamentally rugby consists of a series of intensive workloads that occur during the BIP periods and understanding these workloads and the associated durations will help inform effective training interventions. The importance of establishing WCS to help inform best practice training methods (Delaney et al., 2017; Howe et al., 2020) has spurred a surge in research exploring WCS.

Due to the current limitations in the ability of GPS units to accurately quantify collision demands, we did not include such demands in this study. We explicitly focused on locomotive workloads which potentially poses a limitation to the overall workloads of players represented in our study, as the static exertions, collisions, jumps, pulls and pushes account for a significant proportion of player's overall gameplay demands (Delaney et al., 2017).

The accuracy of the GPS data fluctuates due to the distance covered during data collection (Smith & Hopkins, 2012). Although the older 1-5 Hz GPS units have recorded a high standard error of estimates (SEE) (~25% for 10m, ~10% for 40m and ~ 2% for 500m) (Smith & Hopkins, 2012), research using more modern technology has shown considerable improvements in accuracy (Castellano et al., 2011). Despite the improvements in technology to date, there are still concerns about the accuracy of GPS data recorded over short distances and durations, specifically when it involves rugby specific movements such as swerving, zig-zagging, and side-stepping (Jennings et al., 2010). Howe et al. (2020) examined the catapult 10Hz GPS (OptimEyeTM S5 GPS, firmware version 7.22, Catapult Sports, Melbourne, Australia) and stated that this GPS unit has poor sensitivity for quantifying peak movement measures across epochs of 5-600s. Howe et al. (2020) used the within-subject variation to determine "noise" and calculated large errors (that is, poor sensitivity) from the signal to noise ratio. However, unlike individual sports where athlete's performance is relatively stable, and given that workload typically dictates their finish order, wide ranges in workload can occur in rugby, unrelated to the result. Therefore, rugby player workloads may vary widely due to their tactical approach and opposition. Some rugby teams have tended to record higher locomotion values when losing a match compared to winning (Brett Smith, personal communication). Perhaps in this instance, the best method of determining the accuracy of GPS measures for shorter durations is to compare the GPS measured metric value against the actual metric value, rather than the signal to noise ratio. Validity studies comparing the GPS metric values against criterion measures of that metric have shown that advancements in technology are improving the accuracy. However, despite these improvements, it appears that some of our intensity data must be erroneous such as the intensity distance per minute data, where maximal speeds of over 60km/h were recorded. We debated whether to remove the erroneous data; however, decided to include it as it provides further insights into the limitations within current GPS units. There is evidence that the longer the distance of the GPS data collection, the more accurate it is (Smith et al., 2019). This is likely due to the errors being normally distributed, and therefore, the longer the duration being measured, the greater the likelihood is that enough data will have been collected for the negative errors and positive errors to cancel each other out. Lots of the data in this study was measured over a long distance, with the smallest maximal BIP total distance being 275 meters (*Figure 3.)*, which theoretically has a SEE of approximately 5% (Smith & Hopkins, 2012). It is likely that some small durations of intensity measures <20 seconds may generate an error; however, most research examines GPS error related to distance and not time. Therefore, it is hard for us to assess the error for these small durations.

We decided to leave the positional data recorded for the hooker in, even though data for one of the team's hookers was missing. Due to this missing data, the 'hooker' positional data is dominated by one player, and therefore may not be a full representation of an average hooker's demands. This is an example of how one exceptional individual can potentially alter the team's data. We considered combining the hooker's data with the front row, as this is often done. However, our initial analysis showed the hookers data to be very different from the props, and if anything, their data presented closer to the loose forward and locks. Therefore, we decided to keep the hooker data separate. In addition to this, the team who participated in this study have not lost over several years. Therefore, the data presented in this study may not provide an accurate representation of an average team.

Although rolling-average epoch analysis of less than 1-minute (i.e., 5, 10, 20, 30-s) may provide useful data to help inform high-intensity interval training prescription and monitoring, there are theoretical limitations to the accuracy of the data as mentioned above. There has been a significant body of research regarding WCS that have used GPS units for their data collection, with a fixed-time or rolling-average epoch methodology (Cunningham et al., 2018; Delaney et al., 2017; Owen, 2019; Pollard et al., 2018; Sheppy et al., 2020; Varley et al., 2012). These studies have been published in a variety of peerreviewed, high-quality journals, suggesting that arguably, the scientific community believes that the benefits of this type of research outweigh the possible errors in GPS data collection. This also suggests that researchers are aware of the inherent risks and that readers are still interested in their ability to inform effective training measures from these studies. Therefore, the goal of our research was to explore a potentially more accurate method of examining WCS by quantifying both the MaxBIP metric values in BIP time and within a series of plays fitting into specific epochs.

This study is unique in the way that we have quantified the maximum BIP value across a range of locomotive GPS metrics and positional subgroups. This was done through a BIP analysis as well as a unique rolling-MultiPlay analysis which examined a series of BIP time that fit into epochs of 5 minutes, 10 minutes, 15 minutes and 20 minutes. We also identified the segment of the game that these maximum GPS metric values occurred in to gain insight into the peak period of the game in which players are required to be prepared and conditioned. In contrast to previous research which had utilised a rolling-average epoch methodology (Cunningham et al., 2018; Owen, 2019; Read et al., 2019; Sheppy et al., 2020), we used a rolling-MultiPlay analysis to quantify MaxBIP locomotion values across a range of epoch timeframes, progressively moving along from the start of one play to the start of next play.

Our study presented different results in regards to the peak period segments of the game to those of Owen (2019). As seen in *Figure 2.*, the maximum BIP values for the current study occurred in the last two segments of the second half. In contrast, Owen (2019) had concluded that the 1^{st} segment of each half was where the greatest intensity running demands occurred for both forwards and backs compared to all other segments and that the 1^{st} segment had a greater distance covered than the 5^{th} segment. This was likely due to the differences in methodologies between the current study, and that of Owen (2019). Owen (2019) split their games evenly into 8 periods of roughly 10 minutes each, excluding overtime data that did not fit within each 10 minute segment and excluding players who had played less than 60 minutes of the game. In the current study, each match half was split evenly into 4 quarters of varying lengths, depending on the length of each half. This accounted for all BIP work throughout the game. We also decided to include all players data, regardless of their time on the field, as it was suggested by Lacome et al. (2016) that substitute players have the potential to reach peak GPS metric values, and therefore, we needed to include these player’s data in our research.

In addition to this, players may occasionally be required to work hard during OOP time, such as running to reposition for the next play or a for a tap-ball or quick-line-out. We, however, are specifically focused on the maximum GPS metric values, which are highly unlikely to occur during OOP time. Therefore, while the OOP time was included in our MultiPlay analysis to calculate %W: R, unlike previous studies (Cunningham et al., 2018; Delaney et al., 2017; Owen, 2019; Read et al., 2019; Sheppy et al., 2020), we decided to exclude any work done in OOP time in our study. Although this exclusion contributes to the greater prediction of WCS MaxBIP workloads, it potentially poses a limitation to our study in the way that it may not represent the overall total distance requirements of players.

While we have established the volume and intensity WCS MaxBIP workloads and the WCS BIP workloads across various epoch lengths, there does not appear to be any distinct pattern for when these events occur throughout the game. Therefore, players arguably need to be conditioned to achieve these workloads at any stage of the match. There is a possibility that segments 7 and 8, in *Figure 2.*, may have presented as the peak passages due to substituting players. We believe it is essential for those players remaining on the field to be prepared and capable of performing the workloads required to keep the overall team performing at their peak. Therefore, we believe it is crucial to condition both the full game players and the substitutes accordingly for this high level of maximum work. The WCS results from this study will provide practitioners with useful information to inform BIP workloads, durations and work to rest ratios. These results will provide information around training for both maximal intensity training (BIP analysis), as well as maximal sustainable training workloads (MultiPlay analysis). We believe our rolling-MultiPlay analysis methodology may better inform training practices than previous rolling-average epoch or fixed-time epoch methodologies, as it represents the workloads required during BIP, rather than the average demands over time which have previously been proven to underestimate peak workloads (Pollard et al., 2018; Whitehead et al., 2018).

2.5 Practical Applications

A primary purpose of this research was to demonstrate what a possible WCS training could look like. An example of a BIP WCS drill for HMLD for an outside back, as seen in *Table 3.*, would involve covering 155 HMLD meters within a time frame of 2 minutes 58 seconds. This would mean covering ~52 HMLD meters per minute during this drill.

An example of a 5 minute HMLD WCS drill for a midfield back, as seen in *Table 3.*, the aim would be to accumulate 178 HMLD meters in a time frame of 2 minutes and 11 seconds, with a work to rest of 40%. This could be achieved by performing 3 bouts of ~44 seconds work followed by ~56 seconds rest, with each bout of work set achieve 1/3 of the 178 HMLD meters (~59m), overall equating to ~80 HMLD meters per minute over the 5 minute time frame.

Also seen in *Table 3. a*n example of a 20 minute HMLD WCS drill for a prop would be to accumulate 327 HMLD meters in a time frame of 7 minutes 11 seconds, with a work to rest of 35%. This would involve something like 12 bouts of ~36 seconds of work followed by ~64 seconds rest, with each bout of work aiming to achieve 1/12 of the 327 HMLD meters (~27m), overall equating to ~45 HMLD meters per minute throughout the 20 minute time frame.

Trainers can refer to the metric per minute values for maximum intensity training. In contrast, they can refer to the metric and MultiPlay data, which indicates a more sustainable maximum work output. There was no clear pattern within the data as to where the WCS likely occurs during the game. Therefore, it would be beneficial for players to be conditioned for WCS to occur at any stage of the match. Coaches and trainers should therefore consider adding various WCS drills into the start, middle or end of their training, potentially mixing this timing up across multiple training sessions.

2.6 Conclusion

This study examined data from a professional Japanese rugby union team, intending to determine the WCS BIP and the WCS maximum sustainable workloads for locomotive metrics, and the segment of the game each occurred in during a series of matches over the 2019-2020 seasons. Comparisons were made between sub-positional groups and across a range of locomotive GPS metrics.

This study specifically focused on the single maximum value that each position reached throughout the entire 2 seasons. Therefore, it is likely that our results may overestimate the general locomotive demands in a game. However, this study was aimed at preparing the players to be able to reach those maximum demands when they occur, so trainers can use this research to gain an insight into what these maximum values likely are, and train their players to be prepared to reach them. In conclusion, as no distinct patterns were found as to the segments of the game that the WCS MaxBIP demands occur, we believe that all players need to be conditioned for these peak demands to occur at any stage of the game. This is the first study to our knowledge that has examined the MaxBIP demands as WCS for both BIP time and BIP time throughout a series of plays fitting into various epochs. These results will contribute to existing knowledge and ongoing research on the WCS locomotive workload demands of rugby union players.

References

Akenhead, R., French, D., Thompson, K. G., & Hayes, P. R. (2014). The acceleration dependent validity and reliability of 10Hz GPS. *Journal of Science and Medicine in Sport, 17*(5), 562-566. https://doi.org/10.1016/j.jsams.2013.08.005

Austin, D., Gabbett, T., & Jenkins, D. (2011). The physical demands of super 14 rugby union. *Journal of Science & Medicine in Sport, 14*(3), 259-263.

Cahill, N., Lamb, K., Worsfold, P., Headey, R., & Murray, S. (2013). The movement characteristics of English premiership rugby union players. *Journal of Sports Sciences, 31*(3), 229-237. https://doi.org/10.1080/02640414.2012.727456

Carling, C., & Dupont, G. (2011). Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *Journal of Sports Sciences, 29*(1), 63-71. https://doi.org/10.1080/02640414.2010.521945

Castellano, J., Casamichana, D., Calleja-González, J., Román, J. S., & Ostojic, S. M. (2011). Reliability and accuracy of 10 Hz GPS devices for short-distance exercise. *Journal of Sports Science & Medicine, 10*(1), 233-234.

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Medicine, 43*(10), 1025-1042. https://doi.org/10.1007/s40279-013-0069-2

Cunningham, D. J., Shearer, D. A., Carter, N., Drawer, S., Pollard, B., Bennett, M., . . . Kilduff, L. P. (2018). Assessing worst case scenarios in movement demands derived from global positioning systems during international Rugby Union matches: Rolling averages versus fixed length epochs. *PLoS One, 13*(4), e0195197. https://doi.org/10.1371/journal.pone.0195197

Delaney, J. A., Thornton, H. R., Pryor, J. F., Stewart, A. M., Dascombe, B. J., & Duthie, G. M. (2017). Peak running intensity of international rugby: Implications for training prescription. *International Journal of Sports Physiology and Performance, 12*(8), 1039-1045. https://doi.org/10.1123/ijspp.2016-0469

Deutsch, M. U., Kearney, G. A., & Rehrer, N. J. (2007). Time-motion analysis of professional rugby union players during match-play. *Journal of Sports Sciences, 25*(4), 461-472. https://doi.org/10.1080/02640410600631298

Duthie, G., Pyne, D., & Hooper, S. (2003a). Applied physiology and game analysis of rugby union. *Sports Medicine, 33*(13), 973-991. https://doi.org/10.2165/00007256-200333130-00003

Duthie, G., Pyne, D., & Hooper, S. (2003b). The reliability of video based time motion analysis. *Journal of Human Movement Studies, 44*(3), 259-272.

Duthie, G., Pyne, D., & Hooper, S. (2005). Time motion analysis of 2001 and 2002 Super 12 rugby. *Journal of Sports Sciences, 23*(5), 523-530. https://doi.org/10.1080/02640410410001730188

Duthie, G., Pyne, D., Marsh, D., & Hooper, S. (2006). Sprint patterns in rugby union players during competition. *Journal of Strength and Conditioning Research, 20*(1), 208-214. https://doi.org/10.1519/R-16784.1

Eaton, C., & George, K. (2006). Position specific rehabilitation for rugby union players. Part I: Empirical movement analysis data. *Physical Therapy in Sport, 7*(1), 22-29. https://doi.org/10.1016/j.ptsp.2005.08.006

Howe, S. T., Aughey, R. J., Hopkins, W. G., Cavanagh, B. P., & Stewart, A. M. (2020). Sensitivity, reliability and construct validity of GPS and accelerometers for quantifying peak periods of rugby competition. *PLoS One, 15*(7), e0236024. https://doi.org/10.1371/journal.pone.0236024

Jennings, D., Cormack, S., Coutts, A. J., Boyd, L., & Aughey, R. J. (2010). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *International Journal Sports Physiololgy Performance, 5*(3), 328-341. https://doi.org/10.1123/ijspp.5.3.328

Jones, M. R., West, D. J., Crewther, B. T., Cook, C. J., & Kilduff, L. P. (2015). Quantifying positional and temporal movement patterns in professional rugby union using global positioning system. *European Journal of Sport Science, 15*(6), 488-496. https://doi.org/10.1080/17461391.2015.1010106

Kelly, D., Coughlan, G. F., Green, B. S., & Caulfield, B. (2012). Automatic detection of collisions in elite level rugby union using a wearable sensing device. *Sports Engineering, 15*(2), 81-92. https://doi.org/10.1007/s12283-012-0088-5

Lacome, M., Piscione, J., Hager, J.-P., & Carling, C. (2016). Analysis of running and technical performance in substitute players in international male rugby union competition. *International Journal of Sports Physiology and Performance, 11*(6), 783-792. https://doi.org/10.1123/ijspp.2015-0191

Malone, J. J., Barrett, S., Barnes, C., Twist, C., & Drust, B. (2020). To infinity and beyond: The use of GPS devices within the football codes. *Science and Medicine in Football, 4*(1), 82-84. https://doi.org/10.1080/24733938.2019.1679871

McLean, D. A. (1992). Analysis of the physical demands of international rugby union. *Journal of Sports Sciences, 10*(3), 285-296. https://doi.org/10.1080/02640419208729927

Naughton, M., Jones, B., Hendricks, S., King, D., Murphy, A., & Cummins, C. (2020). Quantifying the collision dose in rugby league: A systematic review, meta-analysis, and critical analysis. *Sports Medicine - Open, 6*(1), 6. https://doi.org/10.1186/s40798-019-0233-9

Owen, S. M. (2019). *Match-play demands of a super rugby team* (Doctor in Sports Science). Stellenbosch University, South Africa. Retrieved from https://scholar.sun.ac.za/handle/10019.1/107217

Peeters, A., Carling, C., Piscione, J., & Lacome, M. (2019). In-match physical performance fluctuations in international rugby sevens competition. *Journal of Sports Science & Medicine, 18*, 419-426.

Pollard, B., Turner, A., Eager, R., Cunningham, D., Cook, C., Hogben, P., & Kilduff, L. (2018). The ball in play demands of international rugby union. *Journal of Science & Medicine in Sport, 21*(10), 1090-1094.

Read, D., Till, K., Beasley, G., Clarkson, M., Heyworth, R., Lee, J., . . . Jones, B. (2019). Maximum running intensities during English academy rugby union match-play. *Science and Medicine in Football, 3*(1), 43-49. https://doi.org/10.1080/24733938.2018.1464660

Reardon, C., Tobin, D. P., Tierney, P., & Delahunt, E. (2017). The worst case scenario: Locomotor and collision demands of the longest periods of gameplay in professional rugby union. *PLoS One, 12*(5), e0177072. https://doi.org/10.1371/journal.pone.0177072

Roberts, S. P., Trewartha, G., Higgitt, R. J., El-Abd, J., & Stokes, K. A. (2008). The physical demands of elite English rugby union. *Journal of Sports Sciences, 26*(8), 825-833.

Roe, G., Halkier, M., Beggs, C., Till, K., & Jones, B. (2016). The use of accelerometers to quantify collisions and running demands of rugby union match-play. *International Journal of Performance Analysis in Sport, 16*(2), 590-601. https://doi.org/10.1080/24748668.2016.11868911

Sheppy, E., Hills, S. P., Russell, M., Chambers, R., Cunningham, D. J., Shearer, D., . . . Kilduff, L. P. (2020). Assessing the whole-match and worst-case scenario locomotor demands of international women's rugby union match-play. *Journal of Science and Medicine in Sport, 23*(6), 609-614. https://doi.org/10.1016/j.jsams.2019.12.016

Smith, B., Tarrant, O., & McIntosh, N. (2019. *Examination of the efficacy of GPS generated metabolic load measures for monitoring intensive intermittent running load in rugby union*. Paper presented at the 23rd Annual Congress of the European College of Sport Science, Dublin, Ireland. Retrieved from https://www.researchgate.net/publication/333816468

Smith, T. B., & Hopkins, W. G. (2012). Measures of rowing performance. *Sports Med, 42*(4), 343-358. https://doi.org/10.2165/11597230-000000000-00000

Theodoropoulos, J. S., Bettle, J., & Kosy, J. D. (2020). The use of GPS and inertial devices for player monitoring in team sports: A review of current and future applications. *Orthopedic Reviews, 12*(1) https://doi.org/10.4081/or.2020.7863

Thornton, H. R., Nelson, A. R., Delaney, J. A., Serpiello, F. R., & Duthie, G. M. (2019). Interunit reliability and effect of data-processing methods of global positioning systems. *International Journal of Sports Physiology and Performance, 14*(4), 432-438. https://doi.org/10.1123/ijspp.2018-0273

Varley, M. C., Elias, G. P., & Aughey, R. J. (2012). Current match-analysis techniques' underestimation of intense periods of high-velocity running. *International Journal of Sports Physiology and Performance, 7*(2), 183-185. https://doi.org/10.1123/ijspp.7.2.183

Whitehead, S., Till, K., Weaving, D., & Jones, B. (2018). The use of microtechnology to quantify the peak match demands of the football codes: A systematic review. *Sports Medicine, 48* https://doi.org/10.1007/s40279-018-0965-6

Williams, J., Hughes, M., & O'Donoghue, P. (2005). The effect of rule changes on match and ball in play time in rugby union. *International Journal of Performance Analysis in Sport, 5*(3), 1-11.

World Rugby. (2019). *Laws of the game rugby union.* Retrieved from https://laws.worldrugby.org/?law=showallbynumbers

Appendices

Appendix 1

Ball in Play (BIP) Rules

STARTS OF PLAY

START OF EACH HALF – Referee's whistle

ALL OTHER RESTARTS – Initiation of kick sequence

> *Note: If there is a kick error, i.e. kicked out on full or not kicked 10m and play stops, the ball was NEVER IN PLAY*

LINEOUT – On release from Hookers hands

QUICK THROW (from out of play kick) – initiation of kick sequence

> (*if quick throw is from an IN PLAY kick, previous ball in play sequence continues)*

SCRUM – ON "Set" – initiation of contact between both front rows

KICK ERROR (missed kick at goal/kick for touch that ends up in play) – initiation of kick sequence

QUICK TAP – Initiation of tap sequence

> *less than 5 seconds after referees whistle will be an extension of play*
>
> *more than 5 seconds after referees whistle will be a new play*

ENDS OF PLAY

BALL IN TOUCH – when touch judge raises flag

TRY SCORED – As ball is touched down

ERROR/PENALTY – when referee blows whistle

ALL OTHER COUNTER/TURNOVER will be same BIP as previous sequence.

Instructions:

1. Create new timeline with just Ball in Play row
2. Adjust start and end times so they match exactly the rules above
3. Duplicate Row and rename "Ball in Play NEW"
4. Drag starts of clips back so there is no time between clips (example on next page)
5. Export as XML
6. Upload XML to Google Drive – rugby teams > Games > XML Files

Do so for all 2019 & 2020 Pre-Season and Competition Games.

Appendix 2

The University of Waikato
Private Bag 3105
Gate 1, Knighton Road
Hamilton, New Zealand

Human Research Ethics Committee
Julie Barbour
Telephone: +64 7 837 9336
Email:humanethics@waikato.ac.nz

THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

23 July 2019

Morgan Haakma
School of Health Sport and Human Performance
By email: mlh361@hotmail.com

Dear Morgan

HREC2019#05 : Exploring and analysing the notion of worst case scenario in rugby union

Thank you for submitting your amended application HREC2019#05 for ethical approval.

We are now pleased to provide formal approval for your project, where you will request permission to use data for your Masters thesis. The relevant data is currently being collected on game play from players of the [Rugby Club] Rugby team [Location of club] and it includes GPS data from matches, and footage of matches coded using Sportscode software.

Please contact the committee by email (humanethics@waikato.ac.nz) if you wish to make changes to your project as it unfolds, quoting your application number with your future correspondence. Any minor changes or additions to the approved research activities can be handled outside the monthly application cycle.

We wish you all the best with your research.

Regards,

Julie Barbour PhD
Chairperson
University of Waikato Human Research Ethics Committee

Appendix 3

The University of Waikato, Te Oranga School of Human Development and Movement Studies

Information Sheet: [Rugby Club] Rugby Players

Research Project Title
Exploring and analysing the notion of worst case scenario in rugby union.

Researchers
Morgan Haakma
Sport Health and Human Performance Masters Student
Ph: +64 27 206 2695
Email: morganhaakma1997@gmail.com

Dr Brett Smith
Te Oranga School of Human Development and Movement Studies Faculty of Education
University of Waikato
Private Bag 3105
Hamilton
Ph (07) 8384466 ext 7863
Fax (07) 8384555
Mob (021) 627863
Email brett@waikato.ac.nz

Experiment Purpose
This research project seeks to explore and analyse the notion of worst case scenario with the aim of gaining a more definite definition of a worst case scenario play in rugby union.

Procedure
Player's GPS data and Sportscode data will be collected during every game over the season, as per normal team protocol. GPS metrics and Sportscode metrics will be analysed to determine the worst case scenario play for each game.

Confidentiality
Confidentiality and participant anonymity will be strictly maintained. Individual participants will not be named, and neither will the team, however, in some cases, player positions relating to certain findings may be mentioned, and it will be mentioned that the team is a professional squad that compete in the Japanese Top League competition. It should however be noted that while every effort is made to ensure confidentiality, this cannot be guaranteed.

Likelihood of Discomfort
The normal matches are rigorous and involve a number of discomforts and some potential risks. The [Rugby Club] seeks to minimise these discomforts and risks through a

comprehensive safety plan, associated monitoring procedures, and employment of specialist medical personnel who are present during every training session and match. This project does not require the players to do anything more or different than what is normally required by the [Rugby Club] for training and matches.

Researcher

Morgan Haakma (Master's student researcher) can be contacted by email at morganhaakma1997@gmail.com or by phone +64272062695 regarding this project.

In addition, Dr Brett Smith (supervisor) can be contacted in room TL 3.01 of the School of Education building at the University of Waikato. He can also be contacted by phone 021 628963 or by email brett@waikato.ac.nz regarding this project.

Resolution of any disputes

If you are unhappy with an aspect of this research please contact the researcher. If you are not happy with how your issues are dealt with and wish to discuss these issues further or make a complaint to a higher authority please contact the Head of Te Oranga School of Human Development and Movement Studies on phone 07 8384500

Results

A Master's thesis will be completed from this research by the end of 2020. A copy of this thesis, generated from this study will be available after this date which can be obtained by contacting the researcher, it will also be sent to the [Rugby Club] Rugby Team upon completion.

Agreement

Your signature on this form indicates that you have understood to your satisfaction the information regarding participation in the research project and agree that your data can be included in a thesis publication. In no way does this waive your legal rights nor release the investigators, sponsors, or involved institutions from their legal and professional responsibilities. You understand you have one week to withdraw from the project once data collection has started and can do this by contacting and informing the researchers. If you have further questions concerning matters related to this research, please contact the researcher, supervisor or the research committee of the Te Oranga School of Human Development Studies, University of Waikato.

The University of Waikato, Te Oranga School of Human Development and Movement Studies

Research Consent Form: [Rugby Club] Rugby Players

This consent form, a copy of which has been given to you, is only part of the process of informed consent. It should give you the basic idea of what the research is about and what your participation will involve. If you would like more detail about something mentioned here, or information not included here, please ask the researcher or research supervisor. Please take the time to read this form carefully and to understand any accompanying information.

Research Project: Exploring and analysing the notion of worst case scenario in rugby union.

Name of Researcher: Morgan Haakma
Name of Supervisor: Brett Smith

By signing below I acknowledge that I have received an information sheet about this research project, or have had the study explained to me by the researcher's supervisor. I have had the chance to ask any questions and discuss my participation with other people. Any questions have been answered to my satisfaction.

I agree to allow my data to be included in this research project thesis and I understand that I have one week to withdraw from the project once data collection has started and can do this by contacting and informing the researchers. If I have any concerns about this project, I can contact the researcher or the Head of Te Oranga School of Human Development and Movement Studies

Participants Name:____

Signature:____________________________ Date:__________

The University of Waikato, Te Oranga School of Human Development and Movement Studies

Information Sheet: Coaches and Management of the [Rugby Club]

Research Project Title
Exploring and analysing the notion of worst case scenario in rugby union.

Researchers
Morgan Haakma
Sport Health and Human Performance Masters Student
Ph: +64 27 206 2695
Email: morganhaakma1997@gmail.com

Dr Brett Smith
Te Oranga School of Human Development and Movement Studies Faculty of Education
University of Waikato
Private Bag 3105
Hamilton
Ph (07) 8384466 ext 7863
Fax (07) 8384555
Mob (021) 627863
Email brett@waikato.ac.nz

Experiment Purpose
This research project seeks to explore and analyse the notion of worst case scenario with the aim of gaining a more definite definition of a worst case scenario play in rugby union.

Procedure
Player's GPS data and Sportscode data will be collected during every game over the season, as per normal team protocol. GPS metrics and Sportscode metrics will be analysed to determine the worst case scenario play for each game.

Confidentiality
Confidentiality and participant anonymity will be strictly maintained. Individual participants will not be named, and neither will the team, however, in some cases, player positions relating to certain findings may be mentioned, and it will be mentioned that the team is a professional squad that compete in the Japanese Top League competition. It should however be noted that while every effort is made to ensure confidentiality, this cannot be guaranteed.

Likelihood of Discomfort
The normal matches are rigorous and involve a number of discomforts and some potential risks. The [Rugby Club] seeks to minimise these discomforts and risks through a

comprehensive safety plan, associated monitoring procedures, and employment of specialist medical personnel who are present during every training session and match. This project does not require the players to do anything more or different than what is normally required by the [Rugby Club] for training and matches.

Researcher

Morgan Haakma (Master's student researcher) can be contacted by email at morganhaakma1997@gmail.com or by phone +64272062695 regarding this project.

In addition, Dr Brett Smith (supervisor) can be contacted in room TL 3.01 of the School of Education building at the University of Waikato. He can also be contacted by phone 021 628963 or by email brett@waikato.ac.nz regarding this project.

Resolution of any disputes

If you are unhappy with an aspect of this research please contact the researcher. If you are not happy with how your issues are dealt with and wish to discuss these issues further or make a complaint to a higher authority please contact the Head of Te Oranga School of Human Development and Movement Studies on phone 07 8384500

Results

A Master's thesis will be completed from this research by the end of 2020. A copy of this thesis, generated from this study will be available after this date which can be obtained by contacting the researcher, it will also be sent to the [Rugby Club] Rugby Team upon completion.

Agreement

Your signature on this form indicates that you have understood to your satisfaction the information regarding participation in the research project and agree that your data can be included in a thesis publication. In no way does this waive your legal rights nor release the investigators, sponsors, or involved institutions from their legal and professional responsibilities. You understand you have one week to withdraw from the project once data collection has started and can do this by contacting and informing the researchers. If you have further questions concerning matters related to this research, please contact the researcher, supervisor or the research committee of the Te Oranga School of Human Development Studies, University of Waikato.

The University of Waikato, Te Oranga School of Human Development and Movement Studies

Research Consent Form: Coaches and Management of the [Rugby Club]

This consent form, a copy of which has been given to you, is only part of the process of informed consent. It should give you the basic idea of what the research is about and what your participation will involve. If you would like more detail about something mentioned here, or information not included here, please ask the researcher or research supervisor. Please take the time to read this form carefully and to understand any accompanying information.

Research Project: Exploring and analysing the notion of worst case scenario in rugby union.

Name of Researcher: Morgan Haakma
Name of Supervisor: Brett Smith

By signing below I acknowledge that I have received an information sheet about this research project, or have had the study explained to me by the researcher's supervisor. I have had the chance to ask any questions and discuss the team's participation in this study with other people. Any questions have been answered to my satisfaction.

I agree to allow the [Rugby Club] player's data to be included in this research project thesis and I understand that players have one week to withdraw from the project once data collection has started and can do this by contacting and informing the researchers. If I have any concerns about this project, I can contact the researcher or the Head of Te Oranga School of Human Development and Movement Studies.

Name:_______________________________________

Signature:___________________________ Date:__________

Appendix 4

MEMO

To	The University of Waikato Human Research Ethics Committee	From	Confidential Head Coach) etc
Organisation	Confidential	Telephone	Confidential
Date	5th July 2019	Email	Confidential
Subject	Confidential support of Morgan Haakma's research project		

The Confident Club endorse and fully support the research project to be undertaken by Morgan Haakma, which is titled "Exploring and analysing the notion of worst case scenario in rugby union".