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The performance analysis of power output in professional male road cyclists

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The Performance Analysis of Power Output in Professional Male Road Cyclists

This thesis is presented for the degree of

Doctor of Philosophy

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Edith Cowan University
School of Medical and Health Sciences
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DECLARATION

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I dedicate this thesis to my Grandfather, a lover of sport, who peacefully passed away in the final months of this thesis

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Supervisory Panel

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Edith Cowan University

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ABSTRACT

Athletes regularly monitor exercise workload in an attempt to improve and maintain exercise performance. Within road cycling, workload is commonly measured using power output. Yet, it is plausible that power output during road cycling is influenced by several factors such as topography, road gradient or rider specialities. If these factors do influence power output they may influence quantification of workload demands. As such, the purpose of this thesis was to improve our understanding of external workload in professional road cycling and describe the factors which influence power output during performance analysis. Specifically, this thesis examined the power output within single stage (1 day, Study One) and multi-stage races (4-21 days, Study Two, Three and Four). The within seasonal changes in power output of professional cyclists were also examined (Study Five).

Study One calculated the frequency distribution of maximal power output (PO_{peak}) values during road cycling events over different topography categories and analysed the power output 600 s prior to PO_{peak} using a new time series analysis called changepoint. Changepoint estimated the four largest statistical changes in power output to find distinct segments. Seven professional male road cyclists (mean ± SD: age 29.5 ± 2.8 y, mass 69.7 ± 5.5 kg, height 182 ± 5 cm) participated in Study One and were all members of a single professional cycling team. It was found that a greater frequency of PO_{peak} values (54%) occurred during flat stages in the final 80 to 100% of race time compared with the previous 0 to 80% race time. Using changepoint, power output was lower (P <0.05) in segment four compared with PO_{peak} in all topography categories (flat: 235 vs. 823 W, semi-mountainous: 157 vs. 886 W and mountainous: 171 vs. 656 W). These results demonstrate that PO_{peak} values occur at differing time points depending on the topography category and that changepoint demonstrated its ability to analyse power output data.

Study Two calculated the maximal mean power (MMP) of professional cyclists from grand tour events. The MMP was examined across various topographies and rider specialities. Study Two also examined the percentage of race time spent in different power output bands between topographies, road gradients and rider specialities. Thirteen male professional cyclists (mean ± SD: age 25 ± 3 y, mass 69 ± 7.5 kg, height 178 ± 0.5 cm) participated in Study Two. MMP for durations longer than 1200 s were greater in semi-mountainous and mountainous stages, when compared with flat stages (1200 s: 5.1 ± 0.2, 5.2 ± 0.3, 4.5 ± 0.3 $W \cdot kg^{-1}$ respectively; P <0.05). Sprinters and climbers spent greater percentage of race time at a power output greater than 7.5 $W \cdot kg^{-1}$, when compared with general classification riders and domestiques (11.3, 11.4, 7.1 and 5.3%, respectively; P <0.05). A greater proportion of race time was spent at a power output above 3.7 $W \cdot kg^{-1}$ when cycling at a road gradient greater than 5% (P <0.05), compared with road gradients 0 to 5% and less than 0%. In conclusion, caution should be taken when comparing MMP between different races of varying topography or rider specialities.

It was found in Study Two that MMP differs between flat and mountainous stages. Given that critical power (CP) can be estimated from MMP values during competition it is plausible that such differences will influence CP estimation. It is also plausible that difference in MMP between flat and mountainous stages is because cyclists are able to produce greater power output uphill rather than on flat gradients. As such, Study Three examined the use of MMP in the estimation of CP when calculated from stages of differing topographies. Also, Study Three compared estimated CP from a flat (mean gradient 0.4%) and uphill (mean gradient 6.2%) field-based test. Data from thirteen professional male road cyclists (age 29 ± 4 y, height 171 ± 0.9 cm, mass 67 ± 8.2 kg) were analysed. No differences (P >0.05) were observed in estimated CP between topography categories. However, a large effects size (d = 0.8) was observed in CP between flat stages and both semi-mountainous and mountainous stages. Estimated CP was 11.6% lower in flat field-based test, compared with the uphill field-based test (5.0 vs. 5.6 $W{\cdot}kg^{-1}$). Study Three demonstrates a large difference between estimated CP from alternative topography categories and from two different gradient specific field-based tests. With an 11.6% difference in CP observed in Study Three between 0 and 6.2% road gradients, Study Four investigated the magnitude of change in 1 and 5 min MMP from grand tour mountain stages. Road gradients of -5% to +5% were compared chronologically from lowest to highest. Seven professional male road cyclists (age 30 ± 4 y, height 169 ± 8 cm, body mass 69 ± 9 kg) from two professional cycling teams were analysed. In total 50 mountainous stages were analysed in Study Four from grand tours between 2011 and 2016. Power output from road gradient -1% was lower (*P* <0.001) in both 1 and 5 MMP compared with 0% (2.4 to 3.3 and 2.2 to 3.1 $W{\cdot}kg^{-1}$, respectively). Power output from road gradient 1% was lower in both 1 and 5 MMP compared with 2% (3.6 to 4.2 and 3.4 to 4.1 $W{\cdot}kg^{-1}$; (*P* <0.05)). These results highlight the need to consider road gradient when using power output for cycling performance analysis.

Study Five described the within-season external workloads of professional male road cyclists for optimal training prescription. Four professional male cyclists (mean ± SD: age 24 ± 2 y, body mass 77.6 ± 1.5 kg, height 184 ± 4.3 cm) from the same professional cycling team were monitored for 12 months. Within three seasonal phases (phase one: Oct-Jan, phase two: Feb-May and, phase three: June-Sept), the volume and exercise intensity during training and racing was measured. Total distance (3859 ± 959 vs 10911 ± 620 km) and time (240.5 ± 37.5 vs 337.5 ± 26 h) was lower (*P* <0.01) in phase one compared with phase two, respectively. Total distance decreased (*P* <0.01) from phase two compared with phase three (10911 ± 620 vs 8411 ± 1399 km, respectively). Mean absolute (236 ± 12.1 vs. 197 ± 3 W) and relative (3.1 ± 0 vs. 2.5 ± 0 $W{\cdot}kg^{-1}$) power output was higher (*P* <0.05) during racing compared with training, respectively. These results highlight the importance in acknowledging the difference in volume and intensity changes during a season.

In conclusion, this thesis demonstrates that cycling power output is affected by multiple factors including topography, road gradient and a rider's speciality. Caution should be taken when interpreting cycling performance analysis using power output measures such as MMP and CP.

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1 CHAPTER ONE

INTRODUCTION

1.1 Overview

This doctoral thesis contains five research studies. A thematic aim underlying all five studies is to improve our understanding of external workload in professional road cycling and describe the factors which influence power output during performance analysis. Specifically, the purpose of this research is to examine factors which influence power output distribution (e.g. topography and road gradient) during a single-stage race, a multiple-stage race and throughout a professional road cycling season. Furthermore, this thesis examines current methods in analysing external workload data and power output used in performance analysis.

1.2 Background

The professional European cycling season runs from approximately February to September, during which time professional road cyclists will compete in single day, multi-day (typically 4-10 days) and 21 day grand tour events (1). Throughout the season, professional road cyclists are required to maintain very high training and racing volumes and intensities, resulting in significant fatigue and physical stress (2, 3), often with little recovery time. Additionally, individual variations in age, sex, psychological, metabolic, hormonal and genetic factors (4) all influence the training stimulus and response. It is, therefore, essential to regularly monitor each individual cyclist's training and racing load for signs of fatigue and/or symptoms of illness and injury (5), which can lead to underperformance.

To date, a range of performance analysis methods and devices have been developed to determine the external and internal load of athletes. The International Olympic Committee consensus statement on load in sport and risk of injury defines external and internal load (6, 7). External load refers to any external stimuli applied by an athlete that is measured independently from their internal characteristics. Internal load of each individual athlete refers to the physiological and psychological responses following interaction with biological and environmental factors (6, 7). The terms external and internal 'workload' will be used for the remainder of this thesis.

There are different ways in which external and internal workload can be measured. The measurement of external workload normally involves quantifying the training and racing of an athlete according to time (8-15), distance (14, 16, 17) and intensity (14, 18, 19). During cycling exercise, this would typically be the mean power output sustained by a cyclist for a given time (e.g. 300 W for 60 min) (20). The internal workload is a measurement of an internal physiological or psychological function such as heart rate, blood lactate, rate of perceived exertion or psychological stressors (4). With the exception of heart rate, measurements of internal physiological function such as lactate or rate of perceived exertion are often difficult to conduct in the field, especially during professional road cycling competition.

Power meters are the most widely used method of measuring external workload for performance analysis in cycling and provide a range of variables, including power output, speed and cadence. Recent power meter devices also have an internal thermometer and barometric altimeter for the measurement of environmental conditions. It is important to measure power output data for the signs and symptoms of overtraining (20) and under performance from high workload (5). However, power output data are stochastic (that is '*having a random probability distribution or pattern that may be analysed statistically but* *may not be predicted precisely*' (21)) and difficult to interpret. From a single 1 hour ride, 3600 data points can be created. This highlights the need for techniques which simplify power output data without the loss of key information.

Simple statistical summary methods such as the mean power output for a stage fail to reflect the stages stochastic power output distribution and metabolic demand. Binning power output data (9, 10, 22) into training and racing zones- that is, categorising power output into smaller manageable sizes, can begin to provide useful feedback to a cyclist which can be easily calculated. An example used in the majority of external load cycling research (9, 10, 15, 18, 23) is to bin data using the accumulated time spent in each zone (e.g. 30% time spent at < 100 W and 70% time spent > 100 W). While binning power output data provides information on the accumulated time spent in various zones, much of this is submaximal (24) and not useful for easy monitoring of changes in a cyclist's exercise capacity. Rather than binning power output data, alternative approaches to understand the maximal exercise capacities of a cyclist include examining the maximal mean power (MMP) curve (25-27) or the critical power (CP) (23, 28, 29). The MMP curve calculates the maximum power produced by a cyclist over any given time (e.g. 350 W for 5 min). The curve starts with the single highest power output value recorded (PO_{peak}) and then plots the maximum power output for each corresponding time point (i.e. PO_{peak}, 5 s, 15 s, 30 s etc.). MMP values are the highest values observed by a cyclist and therefore, may not represent their absolute physiological maximum which can be obtained in a laboratory test. It is not possible to determine if performance during laboratory testing is maximal whereas cyclists will reach maximal values in the field during competitive situations. Further, while field values may not reflect true physiological maximal values, they do present the load experienced by the cyclists which is important in the accuracy in load quantification. Alternatively, the CP model has become a very popular method for modelling endurance performance. The hyperbolic relationship between power output and time or CP measurement, has recently been demonstrated to reflect training-induced changes in a grand tour cyclist (30). Traditionally, to measure CP a 3 min all out test (31, 32) is conducted in a laboratory environment. Recently, researchers have begun developing a valid field-based test to measure CP (23, 33, 34). However, there are several limitation with the CP model in the optimal protocol and length of the test and that it is asymptotic (i.e. the power value at which power output levels out) in nature (30).

To conduct these performance analyses, large volumes of training and racing data are required. This can be particularly challenging as there are limited data available on professional athletes. Furthermore, problems remain with the influence of environmental factors such as temperature, altitude, wind resistance and gradient on performance analysis.

1.3 Statement of the Problem

Despite the relatively easy process of collecting power output data, an understanding of the environment factors influencing performance analysis is limited and presents several issues (35). Firstly, power output is collected from a range of topography categories (flat, semi-mountainous and mountainous). Previous studies have demonstrated changes in power output across different topography categories (9, 10, 15, 23, 36). However, little is known if topography influences performance analysis using power output measures such as MMP and CP. Secondly, several studies have demonstrated that road gradient causes power output to change (37-39). To the author's knowledge, no study has looked at alternative road gradients on performance analysis using power output. Thirdly, recent work has begun to develop a CP field test (33, 34, 40). A valid and reliable CP field test would be useful for both professional and enthusiast cyclists. To date, research using the new CP field test has been conducted in recreational cyclists (33, 34, 40). Therefore, research is warranted using the new test in professional road cyclists.

As well as environment factors, several other factors influence cycling performance. Firstly, power output is stochastic, therefore, methods in reducing the stochastic nature of power output without the loss of important information are needed. Secondly, as well as multiple topography categories, a range of rider specialities exist (sprinter, climber, domestiques and general classification). Very few studies (26, 41-43) have investigated how different riders influence performance analysis. Thirdly, analyses of the seasonal performance of professional male road cyclists are limited in the literature. With the exception of a case study by Pinot and Grappe (44), no detailed performance analysis data exists on the seasonal practices of professional male road cyclists.

1.4 Significance of the Research

This research will improve our understanding of external workload in professional road cyclists. The contribution that this research makes is beneficial to professional and amateur alike. Specifically, the influence of environmental factors on cycling power output used during performance analysis is examined. A greater understanding of performance analysis using power output data will aid in explaining the external workload of racing and training more accurately and ameliorate the need to estimate the physical condition of a rider. Additionally, results from this research will further our understanding of the physiological demands of professional male road cycling. While the physiological demands of professional road cyclists have been documented (1, 13, 45-47), much of this research was based on data collected in the late 90’s and early 2000’s, when doping in endurance cycling was known to be highly prevalent (48). As such, it is plausible that previous performance data provides an over estimation of the requirements within professional road cycling.

However, Lippi et al. (49) have shown that since the introduction of the biological passport, no decline in speed during grand tours has been observed.

1.5 Purpose of the Research

This thesis aims to examine the influence of specific external variables (i.e. topography categories, road gradients and rider specialities) on power output during single, multi-stage and seasonal cycling performance in professional male road cyclists. It also examines current performance analysis methods (i.e. MMP or CP) using power output data and investigates a novel time series based analysis.

The primary purpose of Study One is to describe the frequency distribution of PO_{peak} values from different stage topography categories (flat, semi-mountainous and mountainous). An additional aim of Study One is to use a novel changepoint method to analyse the distribution in power output 600 s prior to PO_{peak} efforts from the different stage topography categories. Determining the distribution of power output and where these PO_{peak} efforts occur will assist our understanding of the demands on professional road cycling during a stage race and maybe identify some of the tactical differences adopted in various stage types.

The primary purpose of Study Two is to examine if MMP obtained from a 21 day grand tour events differs between stages for each topography category and rider speciality. Such findings will provide specific information on the requirements of professional road cyclists from a range of specialities. Furthermore, if MMP is influenced by factors such as topography then other performance analysis measurements using power output may also differ. A further purpose of Study Two is to quantify the time spent in power output zones for each topography, road gradient and rider speciality during 21 day grand tour event.

The purpose of Study Three is to investigate the use of power output for the estimation of CP from different topography categories during a 21 day grand tour. If CP estimated from power output was influenced by different topography categories, CP measurement would be erroneous. In this case, it is plausible that the time spent in different road gradients caused the differing MMP outputs and changes in CP values between topographies.

The purpose of Study Four is to investigate the influence of road gradient on power output obtained from mountainous stages during 21 day grand tours. If road gradient is found to influence power output in Study Four, then this may explain any differences observed in Studies Two and Three.

Finally, the purpose of Study Five is to investigate within-season variation of external workload (i.e. distance and distribution of power output) in a group of professional road cyclists preparing for the world team time trial championships.

1.6 Research Questions & Hypotheses

The research questions (denoted "Q") and corresponding hypotheses (denoted "H") for each study of this thesis are outlined below:

1.6.1 Study One (Chapter Three)

Examining the Distribution of Maximal Power Output Efforts and the Use of Changepoint Analysis in Professional Road Cyclists

Q1: Does the frequency distribution of PO_{peak} values change from stage races of differing topography categories (flat, semi-mountainous and mountainous) in professional road cyclists?

H1: The majority of PO_{peak} values will occur during the final section (> 80%) of flat stage races as the exercise intensity increases towards the finish. Alternatively, during semi-mountainous and mountainous stages, the frequency of PO_{peak} values will be more evenly distributed across the stage races.

Q2: How is power output distributed in the 600 s prior to PO_{peak} values on different topography categories (flat, semi-mountainous and mountainous)?

H2: The distribution of power output will progressively increase during the 600 s prior to PO_{peak} in flat compared with semi-mountainous and mountainous stages. A more even distribution will be observed in power output prior to PO_{peak} in semi-mountainous and mountainous stages.

1.6.2 Study Two (Chapter Four)

Effects of Topography, Road Gradient and Rider Speciality on Maximal Mean Power Output during Professional Cycling

Q1: Do MMP's between 1 and 3600 s differ between topography categories (flat vs. semi-mountainous vs. mountainous)?

H1: Greater power output values in short MMP durations (i.e. 1, 5 and 15 s) will be observed in flat stages, compared with semi-mountainous or mountainous stages. Greater power output values in longer MMP durations (i.e. 1200, 1800 and 2400 s) will be observed during mountainous stages, compared with flat and semi-mountainous stages.

Q2: Does MMP differ between riders of differing specialities (climber vs. domestic vs. sprinter vs. general classification)?

H2: The sprinters will have the greatest maximal power output values in short MMP durations (< 60 s), when compared with domestiques, climbers and general classification riders. Domestiques, climbers and general classification riders will have greater MMP in longer durations (> 300 s), when compared with sprinters.

Q3: Do topography categories, road gradients and rider specialities influence the distribution of race time spent in power output zones?

H3: The distribution of race time in high power output zones will be greater in mountainous stages with steeper road gradients. Domestiques and climbers will display more race time in greater power output zones, when compared with general classification and sprinters.

1.6.3 Study Three (Chapter Five)

Estimation of Critical Power in Professional Road Cycling

Q1: Does estimated CP differ between topography categories (flat vs. semi-mountainous vs. mountainous) from grand tours in professional male road cyclists?

H1: Estimated CP from grand tour race data will be greater in semi-mountainous and mountainous stages compared with flat stages.

Q2: Is CP determined from a field-based cycling test different when conducted on flat-terrain compared to uphill?

H2: CP determined from an uphill field-based test will be greater than a flat-terrain field-based test.

1.6.4 Study Four (Chapter Six)

Road Gradient Influences Cycling Power Output during Grand Tour Mountain Stages

Q1: Does road gradient change one and five min MMP output in professional male cyclists from mountainous stages obtained from grand tour events?

H1: Power output will increase in relation to increases in road gradient for both one and five MMP.

1.6.5 Study Five (Chapter Seven)

The Within-Seasonal Distribution of External Training and Racing Workload in Professional Male Road Cyclists

Q1: How does external workload vary within-season in professional road cyclists preparing for the world team time trial event?

H1: A greater external load will be observed during the season at the point when major competitive events occur (i.e. greater during a grand tour) whereas, the external load will be lower during the off-season.

1.7 Definition of Abbreviations

Unit or Term	Abbreviation
analysis of variance	ANOVA
anaerobic work capacity	AWC
beats per minute	bpm
confidence interval	CI
critical power	CP
degrees Celsius	°C
fraction of inspired oxygen	F_IO_2
functional threshold power	FTP
maximum heart rate	HR_{max}
hour	h
kilometre (s)	km
kilometres per hour	$km \cdot h^{-1}$
kilojoule	kJ
lactate threshold	LT
minute (time)	min
minutes per day	$min \cdot d^{-1}$
meter	m
millilitres per kilogram per minute	$mL \cdot kg^{-1} \cdot min^{-1}$
maximal mean power	MMP
power output peak	PO_{peak}
revolutions per minute	rpm
second (time)	s

standard deviation	SD
Schoberer Rad Messtechink	SRM
total elevation gain	TEG
maximal oxygen uptake	$\dot{V}O_{2max}$
watt balance model	W'_{bal}
watt	W
watts per kilogram	$W \cdot kg^{-1}$

2 CHAPTER TWO

REVIEW OF THE LITERATURE

2.1 Introduction

Professional road cycling is a complex and dynamic sport, with a range of race categories or competition types, topography categories and rider specialities (Table 2.1). Briefly, competition types are heavily influenced by the duration of the race. Races range in duration from one to twenty one days. Road cycling competitions are also often categorised into mass-start events or time trial events (i.e. individual or team time trials). Single day mass-start races or stages have historically been categorised according to the topography in which the race is conducted (9, 10, 15, 36). Given the complex race categories, competition types, topography categories and environments in which road cycling is performed, athletes typically have specialised roles within a cycling team. Rider specialities are predominantly based upon an individual's physiological characteristics and area of strength. To date, several differing rider specialities have been documented within the literature (sprinter, climber or uphill rider, domestiques, all terrain, time trial and general classification) (1, 26, 41-43). The complex nature of road cycling and various roles of individual athletes, makes performance analysis within professional cycling difficult. Yet, understanding the diversity of these external variables and their influence on the external workload of professional road cycling will improve our understanding of the physical demands placed upon cyclists. Such findings are important in athlete preparation, talent identification and performance analysis.

Table 2.1: The classification of cycling competition types, topography categories and rider specialities.

Competition Types	Topography Categories	Rider Specialties
Grand Tours	Flat	Team/Tour Leaders
Multi-Stage races	Semi-mountainous	Sprinters
Single-Stage races	Mountainous	Climbers
Time Trial		Domestiques

Various portable electronic devices have been developed to provide information on both the external and internal workload measurements during cycling exercise. These devices continuously monitor power output, heart rate, cadence, speed, elevation and temperature (35). A portable electronic device which attaches to a bicycle specifically measuring power output is called a power meter. Power output is an extremely important measure within cycling as it provides a direct assessment of the work or energy expended by a cyclist. Within the past ten years there has been a dramatic increase in the number of commercially available power meters. These power meters measure or estimate power output based on a range of different methods including calculations from wind speeds, chain tensions, and strain gauges built into the pedal, crank, or rear wheel/hub of the bicycle. The reliability and accuracy of these monitors have been shown to vary. Several methods or systems provide much higher accuracy than others. The SRM power meter is often regarded as a gold standard meter due to its accuracy and early development (50). When calibrated, SRM power meters are accurate to within approximately 2% (51).

The ability to accurately quantify work from power output makes cycling a unique sport in terms of the level of understanding possible on the demands of training and racing (35).

Despite the importance of measuring power output it is complex and difficult to analyse. As a result, the core business of several commercially available software companies (e.g. Training Peaks and Golden Cheetah) is to aid in the interpretation and analysis of power output data.

Cycling power data is typically collected at a fast sample rate (1Hz or faster) and can result in extremely large data files from a single training session or race. Along with the large number of training sessions and races performed by cyclists, this has resulted in difficult to interpret datasets. As a result, scientists, coaches and athletes have explored data reduction methods to improve interpretation (30). A simple method is to calculate the average power output over a single duration. However, this approach does not demonstrate the stochastic nature of power output from stage racing (35). For example, a flat stage with little variance in power output may result in a mean power of 270 W. Alternatively, a stage with undulating topography may require periods of very high and low power output, and result in a lower average power output of 255 W.

These data reduction methods can simplify the data and ease interpretation and understanding. However, an oversimplification of the data can lead to considerable misinterpretation. Several data reduction methods have been developed to better understand the highly stochastic nature of power output including normalised power (35), maximal mean power (26, 27) and exposure variation analysis (8).

Initially, this review will highlight the different ways to monitor workload in professional road cyclists from an internal and external perspective. Following, this review will more specifically highlight how external factors influence power output and describe the methods used to analyse cycling performance.

2.2 Workload Monitoring in Professional Road Cycling

Professional cycling is a dynamic and complex sport. As such, the workload demands of competition and training require prolonged periods of low-intensity cycling, numerous short and explosive high-intensity efforts and sustained periods of high-intensity cycling. These periods result in stress and if prolonged can cause overtraining syndrome which decreases performance (52). Workload has been separated into what has been defined as internal and external load (6, 7). This section introduces the various methods of assessing internal and external workload in road cycling.

2.2.1 Internal workload

Each individual athlete will have a physiological and psychological response to exercise and environmental factors, referred to as 'internal load' (6, 7). This section introduces the measurements of internal workload and describes how they relate to professional road cycling performance. Specifically, the use of $\dot{V}O_{2max}$, heart rate and RPE will be discussed. The influence of external factors including stage type and environmental temperature will also be discussed as these both influence the internal physiological stress of a cyclist.

An athlete's $\dot{V}O_{2max}$ is the maximum amount of oxygen the body can consume (53, 54), and it is closely associated with maximal aerobic capacity. Professional road cyclists demonstrate extremely high aerobic capacities with males exhibiting $\dot{V}O_{2max}$ values ranging from 69.7 to 84.8 $mL \cdot kg^{-1} \cdot min^{-1}$ (1) whereas females exhibit a range between 57 to 64 $mL \cdot kg^{-1} \cdot min^{-1}$ (22). $\dot{V}O_{2max}$ has been demonstrated to separate different types of professional male road cyclists. In a study by Lucía et al. (42) on the physiological responses of professional male road cyclists, climbers had a significantly greater $\dot{V}O_{2max}$ than time trialists; 78.6 ± 2.0 $mL \cdot kg^{-1} \cdot min^{-1}$ vs. 72.0 ± 2.6 $mL \cdot kg^{-1} \cdot min^{-1}$ respectively. During the *Tour de France* and *Vuelta a Espana*, professional male road cyclists have recorded long periods of time near $\dot{V}O_{2max}$ with up to 93 min of flat and 123 min of mountainous stages (32% of total stage time in flat and 40% in mountainous stages) riding greater than 70% of $\dot{V}O_{2max}$ (11). Furthermore, another study recorded the percentage time over ventilatory thresholds (VT_1 and VT_2) (55). Ventilatory thresholds obtained from a $\dot{V}O_{2max}$ test have been demonstrated as an accurate performance level indicator during cycling exercise (56). Specifically, VT_1 is represented as the first increase in minute ventilation that is proportional to CO_2 output whereas, VT_2 is represented as the point at which blood lactate increases considerably and hyperventilation occurs (56). Cyclists have been shown to spend 71 h (70%) below VT_1 and 8 h (7%) of *Tour de France* race time at VT_2 with 23 h (23%) of time spent in between (VT_1-VT_2) (55). While the percentage of time at $\dot{V}O_{2max}$ and above thresholds provides detailed information on the internal workload, scientists commonly use heart rate which is correlated with $\dot{V}O_{2max}$ intensity zones to measure internal workload during professional road cycling events (55, 57).

Heart rate can be used to prescribe and monitor exercise intensity (58). At the beginning of a season, a single laboratory exercise test can provide heart rate zones as a reliable indicator of exercise intensity such as $\dot{V}O_{2max}$, lactate threshold and the first and second ventilatory thresholds (56). Under those circumstances, regular laboratory exercise testing is required to continually update metabolic zones and thresholds as physiological adaption occurs during training and racing. For example, Lucía et al. (56) investigated the stability of target heart rate values corresponding to metabolic thresholds including lactate and first, and second ventilatory thresholds, in thirteen professional road cyclists during a season. Three ramp $\dot{V}O_{2max}$ tests were conducted during the season (rest (November), pre-competition (January) and competition (May) periods). Significant improvements were observed in power output at lactate threshold (LT), VT_1 and VT_2 (Power output at LT: 319 ± 10, 350 ± 8 and 379 ± 9 W; power output at VT_1 321 ± 8, 338 ± 10 and 350 ± 8 W and at VT_2; 411 ±

11, 428 ± 11 and 436 ± 10 W during rest, pre-competition and competition periods respectively) as well as slight changes in the target heart rate, (Heart rate at LT: 154 ± 3, 152 ± 3 and 154 ± 2 bpm; heart rate at VT_1: 155 ± 3, 156 ± 3 and 159 ± 3 bpm; and heart rate at VT_2: 178 ± 2, 173 ± 3 and 176 ± 2 bpm during rest, pre-competition and competition periods respectively). This study by Lucía et al. (56) demonstrates that a single laboratory testing session during the season would be adequate to prescribe training load based upon heart rate in elite endurance athletes.

Research using $\dot{V}O_{2max}$ and heart rate during cycling exercise is confounded by several factors. $\dot{V}O_{2max}$ is influenced by a decrease in the fraction of inspired oxygen as altitude increases. Mountain stages are conducted at moderate altitudes (1500 - 2500 m), therefore, a decrease in $\dot{V}O_{2max}$ occurs resulting in a lower power output demonstrated by several laboratory studies (59-61) and a recent multi-stage field study (62). It is likely that the decrease in power output is due to the decline in oxygen availability at the muscular level. Heart rate is influenced by several factors with up to a 6.5% daily variation being demonstrated in submaximal heart rate (63). These factors include cardiovascular drift, cold environments, altitude and longitudinal adaptive changes during grand tours (58, 64). Cardiovascular drift is the gradual decrease in stroke volume and increase of heart rate (65). Factors which contribute to cardiovascular drift include dehydration, hyperthermia and peripheral vasodilation (58). Exercise in cold environments result in decreases in skin blood flow and increases in metabolic rate. Similar to $\dot{V}O_{2max}$, altitude influences heart rate with submaximal heart rate increasing while $\dot{V}O_2$ remains stable (58). Finally, physiological adaptation occurs over time, however, Lucía et al. (56) demonstrated that heart rate remains stable in professional road cyclists during the course of a season.

Given these confounding factors, caution should be taken when analysing heart rate as a measurement of internal workload. The influence of environmental temperature on endurance cycling exercise performance is well documented within the literature (66-68). Exposure to hot environments for long periods of time cause significant impairment on exercise performance resulting from thermal strain (64, 69, 70) and large endogenous heat production (71). While multiple studies have investigated the influence of heat on cycling performance (68, 72, 73), few have looked at cycling performance with a dynamic component replicating the demands of field-based road cycling studies (8, 9, 23, 74).

RPE measures an athlete's perception of exertion (in some cases perception of effort (75, 76)) and is commonly used within sports science literature for monitoring, prescribing, regulating exercise intensity, and assessing training load (77). The majority of research using RPE as a measurement of exercise intensity has been completed in team sports. Specifically, the approach was demonstrated to be effective in basketball (78) and soccer (79). Several studies have been conducted into the use of RPE and exercise intensity in competitive (80, 81) and professional road cyclists (44, 82). These studies have assessed RPE at the end of training or competition, which is known as session RPE (4, 20). Session RPE is a method of quantifying training load whereby an athletes RPE (on a 1-10 scale) is multiplied by the duration of the session (in minutes) (78). Specifically, Rodríguez-Marroyo et al. (83) analysed the heart rate and session RPE of twelve professional road cyclists from 5, 7 and 21-day races to quantify competition load. The session RPE of cyclists was measured approximately 30 min after the end of each stage using the 0 to 10 RPE scale (84). Interestingly, mean session RPE was significantly greater in 21-day stage races (5.9 RPE) compared with 5 and 7 day races (5.1 and 5 RPE respectively). The 21-day stage races also showed significantly lower maximal (183 ± 1 vs. 186 ± 1 and 187 ± 2 bpm for 21, 5 and 7 day races respectively) and mean heart rates (141 ± 1 vs. 146 ± 1 and 148 ± 3 bpm for 21, 5 and 7 day races respectively). Numerous laboratory studies have highlighted that session RPE may be extremely important in monitoring fatigue during cycling exercise (73, 85-87). However, unlike team sports, it is difficult to obtain session RPE intermittently (i.e. half or quarter time) during cycling races.

In conclusion, the internal workload can be measured in professional road cyclists but, measurements are difficult to conduct in the field except for heart rate. Heart rate provides information on the exercise intensity and physiological stress experienced by a cyclist. Session RPE provides an alternative measurement of internal load for monitoring exercise intensity and can be recorded at the end of any race or training session.

2.2.2 External workload

The term 'external load' refers to any external stimuli produced by an athlete that is measured independently from their internal characteristics (6, 7). Data can be collected from the cyclist's using portable electronic devices (i.e. power output, cadence or speed). This section begins by assessing the reliability of the SRM power meter (within this thesis, all experimental data were collected using SRM power meters) before introducing external workload measurements (i.e. power output and cadence).

Power output is calculated throughout training and professional road cycling races using a portable electronic device called a power meter. Examples of commercially available power meters on the market include Schoberer Rad Messtechink (SRM), PowerTap and Ergomo Pro. These power meters provide a range of external workload variables including power, speed and cadence. As well as these external workload variables, the SRM power meter has been demonstrated to provide an accurate estimation of energy expenditure (88). Energy expenditure is calculated from the knowledge of power output and gross efficiency. This provides useful information for professional road cycling teams to monitor their individual riders given the demand in maintaining hydration status (89, 90), energy intake and expenditure (91-95).

It is important for cyclists and coaches to be confident in their power meter and that the data provided is accurate and reliable. The reliability of the SRM has been assessed in multiple studies (45, 51, 96, 97) described in table 2.2. These studies assess reliability using a range of performance trials including constant power output, sprint tests and field tests. For example, Gardner et al. (51) compared SRM vs. Powertap power meters demonstrating a reduced reliability (increased variability) of the SRM with temperature (2.3 vs. 5.2% respectively). The finding that both SRM and Powertap power meters were sensitive to temperature changes has implications for field data interpretation. The authors recommend re-setting the off set back to zero at regular intervals when temperatures change throughout a ride. Furthermore, Wooles et al. (50) used a static method for obtaining a calibration factor from 153 SRM bicycle power cranks. Using a known mass and lever arm to apply torque load, output frequencies are used to calculate the calibration factor. The authors accepted a reproducibility of ± 0.01 Hz/Nm (i.e less than 1W per 1000W), however, identified a drift -0.15 W with a standard deviation of 1.51 W. Calibration every six months is recommended due to measurement drift in the calibration factor over time. If calibration procedures are adhered to, researchers can have greater confidence in their findings.

Table 2.2: Studies assessing the reliability of the SRM (Schoberer Rad Messtechink) power meter compared with other commercially available power meters.

Author	Participants/devices	Comparison vs. SRM	Reliability Trials	Results
Gardner et al. (51)	19 SRM, 5 PT	PT vs. SRM	Average power (50 - 1000 W) Cadence (60,80,100,120 rpm) Temperature (8 & 21 ^{o}C) Time (1 h - 300 W)	Mean error in average power; SRM 2.3 ± 4.9% & PT -2.5 ± 0.5%. No difference in cadence or time. Temperature did influence power; SRM 5.2% & PT 8.4%.
Bertucci et al. (96)	*n* = 1, national level cyclist	PT vs. SRM	Sub-maximal incremental intensity's (100 - 420 W), cadence (45 - 120 rpm), cycling position (standing or seated), continuous trial (30 min), maximal sprints (8 s) and road cycling event.	Mean error in average power sub-maximal intensity's (-1.3 ± 1.3%).
Franklin et al. (98)	*n* = 8	Monark vs. SRM	60 rpm, 3 kg for 5 min	Monark overestimates power compared with SRM system.
Hurst & Atkins (99)	*n* = 12 trained male cyclists	Polar vs. SRM	3 min intermittent cycle test containing 12 all-out efforts, separated by passive recovery between 5 to 15 s	Mean power; SRM 556 ± 102 W % & Polar 446 ± 61 W.
Duc et al. (97)	*n* = 1, regional level cyclist	EP vs. SRM/PT	Eight sub-maximal incremental tests (100 - 400 W), eight 30min sub-maximal constant power test (180 W), eight sprint tests (> 750 W)	Mean error in average power output; EP-SRM 6.3 ± 2.5%, EP-PT 11.1 ± 2.1%. Mean error in sprint power output; EP-SRM 1.6 ± 2.5%, EP-PT 3.2 ± 2.7%. Mean

Author	Participants/devices	Comparison vs. SRM	Reliability Trials	Results
			and eight field performance training sessions.	error during field performance; EP-SRM 12 ± 5.7%, EP-PT 11.1 ± 2.1%.
Abbiss et al. (45)	*n* = 15 (only for 30 km time trial)	Velotron Ergo vs. SRM	Two sustained constant power trials (250 & 414 W), two incremental power trials & three high-intensity interval power trials, 30 km performance time trial.	< 1% error in constant power trials. High-intensity interval power trials less accurate (Velotron 3% % SRM -2.6%). Velotron was 3.7 ± 1.9% greater than SRM.
Bouillod et al. (100)	*n* = 1 national-level male competitive cyclist	PT, STG and VCT vs. SRM	Three laboratory cycling tests including a sub-maximal incremental tests, as 30-min sub-maximal continuous and a sprint test. Vibrations were also tested in the laboratory and field settings.	Power output for STGA was lower (-5.1%) than SRM during heavy exercise and VCT lower (-4.5%) than SRM during moderate exercise

(SRM, Schoberer Rad Messtechink power meter; PT, PowerTap power meter; EP, Ergomo Pro; Polar, Polar S710 heart rate monitor, and power sensor kit; Monark, Monark 824E); STG, Stages; VCT, Garmin vector).

The accuracy and reliability of power output produced by a power meter is important as the resulting data are used to measure and monitor external workload. Numerous observational studies have examined the direct power output produced by professional male and female cyclists in competition (8-10, 15, 18, 36). Vogt et al. (18) evaluated the power output of six professional male cyclists over a 6 day multi-stage professional road race. Vogt et al. (18) found that cyclists spend the majority of the race time (58%) during mass-start stages at intensities near lactate threshold (220 ± 22 W). Within the multi-stage race, power output during an uphill individual time trial was recorded considerably greater (392 ± 60 W). Indeed, the demands of professional road cycling are dependent on numerous factors including the race format (i.e. time-trials, short circuit of criterium events or longer road races (8)), topography categories (semi-mountainous vs. flat stages; Table 2.1) (10) and race dynamics (i.e. team and individual tactics) (74).

In longer grand tour stage races, little actual direct power output data are available (Table 2.3). Specifically, Vogt et al. (15) documented the power output demands from fifteen professional road cyclists from the 2005 *Tour de France*. The authors found a trend of increasing power output from flat (218 ± 21 W) semi-mountainous (228 ± 22 W) to mountainous (234 ± 13 W) stages. It could, therefore, be suggested that the more mountainous the stage, the greater power output demands are required. In a follow up study by the same research group, Vogt et al. (36) attempted to illustrate the varying power output between flat and mountainous stages in a single professional road cyclist from the *Giro d'Italia*. Mean power output was lower (132 ± 26 W) for flat stages compared with mountainous stages (235 ± 10 W). While these studies highlight the mean power output demands during grand tours, they fail to provide any insight into the stochastic nature of power output. Previous research has characterised flat stages to be more variable in power output due to short bursts of high power (74) whereas, mountainous stages observed showed a constant power output for extended periods of time. Future research should aim to develop methods in reducing power output data into smaller concise data points which can still highlight important changes in load.

Measuring power output is important for the monitoring of workload in professional road cyclists. While power meters are becoming more common, limitations or issues still exist (i.e. calibration or complex noisy data). For example, multiple field studies from professional road races have been conducted using power meters (Figure 2.2) however, their level of accuracy for detecting important changes in professional road cyclists still presents an issue (30). The data are most meaningful when relative to physiological characteristics (% of time at VO_{2max} or heart rate), which is why studies have tried to model power output (55, 56, 101, 102).

Table 2.3: Field studies comparing direct power output differences between flat and mountainous road cycling stages in professional cyclists (male and female).

Study	Participants (*n*)	Stage (*n*)	Age (y)	Height (cm)	Body Mass (kg)	$\dot{V}O_{2peak}$ (mL·kg^{-1}·min^{-1})	Flat mean power output (W)	Hilly/mountainous mean power output (W)
Ebert et al. (9)	*n* = 15 national female road cyclists	World Cup races (flat *n* = 19: hilly *n* = 8)	24.1 ± 4.0	168.7 ± 5.6	57.9 ± 3.6	63.6 ± 2.5	169 ± 17	192 ± 21
Ebert et al. (10)	*n* = 31 national male road cyclists	6 year *Tour of Down Under* (flat *n* = 38: hilly *n* = 37)	20.9 ± 0.4	177 ± 0.4	69.8 ± 2.8	74.0 ± 2.4	188 ± 30	203 ± 32
Vogt et al. (36)	*n* = 1 male professional cyclist (case study)	*Giro d'Italia* (flat *n* =5: mountainous *n* = 4)	26	172	67	-	132 ± 26	235 ± 10
Vogt et al. (15)	*n* = 15 professional cyclists	*Tour de France* (flat *n* = 55: semi-mountainous *n* = 45: mountainous *n* = 48)	29 ± 4.0	181 ± 7	72 ± 7	-	218 ± 21	234 ± 13 (semi-mountainous: 228 ± 22)

During road races cadence is freely chosen. It is the selection of the cyclist rather than a specific cadence being dictated (103). The most optimal cadence depends on the task (104). As task demands change so does the optimal cadence. The most optimal cadence for cyclists is one that minimises metabolic cost (105), reduces muscular stress (103) and perception of effort (103, 104, 106). The optimal cadence adopted by cyclists in the field is debated within the literature (103, 107). Research suggests that professional road cyclists adopt high cadences of between 80 to 100 rpm (103), contrary to the metabolically optimal cadence of between 50 to 70 rpm (107) recorded in triathletes. The optimal cadence chosen is influenced by a range of factors including aerobic fitness, biomechanical, hemodynamic and exercise duration (103, 108). Interestingly, laboratory research has recently shown that with an increased gradient lower cadences were adopted (109). In the field, several studies have demonstrated a preferred higher cadence during flat compared with mountainous stages (15, 110). One reason for the observation of lower freely chosen cadences while cycling uphill is believed to be due to the crank inertial load of cycling. The crank inertial load is the quadratic function of a bicycle's gear function ratio (111). Cyclists change gear ratio according to road gradient, thus influencing the choice of pedal cadence. For example, a cyclist's speed will decrease during uphill cycling resulting in the selection of a low gear ratio whereas, horizontal cycling will lead to high speeds and requires the selection of a high gear ratio (112). Sassi et al. (113) observed ten professional cyclists and reviewed 6 to 8 of their hardest training sessions ranging on road gradients from -4% to 12%. They found a linear decrease in freely chosen cadence as road gradient increased. This decrease appeared to be related to a reduction in speed as a result of increased gradient. Therefore, the crank inertial load is affected by the freely chosen cadence. This in turn, has an impact on the amount of time spent on the pedal, resulting in a change to the required power output.

It could, therefore, be speculated that power output would be change due to this requirement, influencing power output data.

In conclusion, the external workload of professional road cyclists can be measured during cycling using reliable portable electronic devices (Table 2.2). These devices provide a wealth of information including direct power output and freely chosen cadence in which coaches, cyclists and enthusiasts can analyse performance. Nevertheless, the choice of performance analysis is required with multiple options available.

2.3 The Dynamics of Professional Road Cycling

Professional road cycling can be classified into competition types, topography categories and rider specialities (Table 2.1). This section describes the characteristics and workload demands within each classification. An understanding of the different factors (Table 2.1) is required before we describe how to monitor and analyse the workload demands.

2.3.1 Competition types

During a single cycling season, professional male road cyclists can expect to race between 60 and 100 days of the year and, together with training, cover exceptionally long total distances (~ 35000 km) (3). In season competitions vary from single time trials (~ 20 - 100 km), single-day races (~ 60 - 270 km), multi-stage races (~ 3 - 10 days) and grand tours (21 days) (114). This section discusses the characteristics and workload of each competition.

The time trial event can be a single event or integrated into a multi-day tour race (115). These races either involve an individual (individual time trial) or team (team time trial) completing a set distance (e.g. 20 km) in the least amount of time possible. Alternatively, special one-off events have been staged where riders attempt to cover as much distance as possible in a single hour. Rider/s have been reported to hold power outputs in the range of 320 to 450 W during time trials ranging from 5 to 100 km (3), while Chris Boardman averaged an estimated 442 W and an average speed of 56.3 $km \cdot h^{-1}$ when previously breaking the 1 hour cycling record (114). Jacobs et al. (116) analysed the key physiological determinants for optimal time trial performance. They concluded that the key requirements were for a high capability in oxygen transport, high maximal oxygen uptake ($\dot{V}O_{2max}$) and haemoglobin mass (Hb_{mass}) also, increased oxygen, oxidative phosphorylation and electron transport system capacities. Studies on pacing have indicated that performance during the time trial is largely influenced by these physiological characteristics (117-119). It has also been shown that performance during time trials of an extended duration (> 2 min) are typically optimised with an even pacing strategy compared with a negative, all-out, positive, parabolic-shaped and variable pacing strategies (117). However, most studies into pacing and cycling have been conducted in laboratory settings (118, 120-127). There are only a few studies which have been conducted in field settings (128-130) where, pacing and performance during the time trial is largely influenced by both physiological characteristics and various external environmental conditions.

External environmental conditions demonstrated to influence time trial performance include topography (131-133), gradient (131, 134, 135), temperature (136-138) and wind speed (121, 132). Studies using mathematical models have shown that varying power output can be detrimental during a flat, windless 40 km time trial performance (132, 139, 140). During stages of varying gradient, adjusting power output in conjunction with changes in gradient can improve time trial performance (132-134, 139). These studies demonstrate that performance can be improved by slightly increasing power output on uphill and headwind segments and a reduction in power during downhill and on tailwind segments of a time trial. However, in the field cyclists appear to have difficulty maintaining these optimal requirements (135, 139). This is thought to be due to mechanical and/or skill limitations (135) and an inability to physiologically maintain the required power output (139). Rather than mathematical models, more studies are required into the actual practices of professional road cyclists during the time trial. While these studies acknowledge topography, gradient and wind, the environmental temperature must also be considered.

While it has been well documented that thermoregulation and heat stress can influence pacing and time trial performance (137, 138, 141), few studies have examined how performance can be optimised in such conditions. Abbiss et al. (136) compared different starting pacing strategies by ±10% power output in a 20 km cycling time trial performed in the heat (32.7 °C). The authors found no differences in 20 km performance time by manipulating starting power output either 10% above or 10% below that of a self-paced trial. Therefore, while it is clear that environmental temperature may influence optimal pacing, no studies have been able to take this variable into account when developing or modelling optimal profiles. It is likely that this is because of the complexity of thermoregulation. Indeed, fatigue in the heat is believed to be most closely related to internal body temperature which can differ greatly from skin and environmental temperature. Research is needed in quantifying core body temperature during exercise before this variable can be accounted for in fatigue and performance models. Overall, these studies indicate that several environmental factors may influence power output distribution during cycling. While research has begun to examine how some of these factors may influence time trial performance and exercise capacity, more research on actual cycling events is required.

Mass-start one-day races are a single race often, but not always, performed over a circuit of set repeated laps. Important one day races are performed at the Olympics, World Championships, World Cup series and multiple famous one-day classic races (e.g. Paris - Roubaix, Milan - San Remo and Liège - Bastogne - Liège). These events start with a large number of competitors (e.g. 200 riders started the 2016 Paris - Roubaix) and, unlike the time trial where the objective is to finish as quickly as possible, the objective here is to simply cross the finish line ahead of your opponents. As a result, tactics become an extremely important aspect of such races. Such tactics and the capacity to draft behind opponents and team members also has a considerable influence on the race. To the author's knowledge, no study has described the demands of one-day races in professional male road cyclists. However, a few studies exist in female cyclists (8, 9, 142). Ebert et al. (9) compared the average power output from 19 flat and 8 hilly world cup road races in fifteen professional female road cyclists. Average power output was greater in hilly (3.3 ± 0.3 W·kg^{-1}) compared with flat (3.0 ± 0.4 W·kg^{-1}) stages during World Cup road races. This study highlights that topography influences the demands placed on female cyclists during mass-start road races. However, few studies have extensively examined the influence of topography and gradient on performance within one day road cycling. Furthermore, given that the study by Ebert et al. (9) only provides average data on varying sections of a race, it is unclear if such differences are due to the race demands or differences in maximal exercise capacities.

Multi-stage races typically consist of racing over 3 to 10 days, sometimes with multiple stages in one day. The workload demands required to complete each professional multi-day road racing event have been shown to influence performance. Specifically, the length of the stage may influence performance. For example, Rodríguez-Marroyo et al. (14) examined the average heart rates of thirty professional male road cyclists from three (5-day, 8-day and 21-day) alternative stage race lengths. They found that the average time spent in zone three (above respiratory compensation point) was significantly greater in 5-day (~ 31 min) stage races, compared with eight (~ 28 min) and 21 (~ 14 min) day stage races. Gradient may also influence performance. For example, Vogt et al. (18) described the power output demands during multi-stage racing in six professional male road cyclists at the Regio-International road race. The authors found that average power output was 3.4 ± 0.3 W·kg $^{-1}$ for the six day stage race. Interestingly, with the removal of an uphill time trial in the race, average power output was measured 0.3 W·kg^{-1} lower at 3.1 ± 0.2 W·kg^{-1} This removal of the data highlights the possible influence of uphill cycling exercise on power output.

The tactics within a multi-stage race largely depend on the race demands/characteristics and the individual or teams objectives for that race (e.g. stage wins, mountain or sprint classifications and general classification). For instance, teams may specifically target the general classification and not focus on individual stages wins within a multi-stage event. Alternatively, a cyclist may deliberately conserve energy throughout the race in order to reach the final sprint in the best position for the win. Breakaways are also common within multi-stage races in an attempt to win the stage, gain individual and team media exposure or gain intermediate mountain/sprint points (74). Few breakaways will be maintained for the whole duration of the day due to fatigue, team tactics, and race dynamics. Indeed, Menaspà et al. (143) investigated the correlations between the total elevation gain (TEG) and bunch dimensions and demonstrated that the greater the TEG in a stage (i.e. mountainous stages), the greater the likelihood there was for a successful breakaway. Furthermore, it was observed that stages with lower TEG were more likely to end in a bunch sprint. These results highlight the importance of topography on tactical decisions and task demands within multi-stage racing. With the exception of a few studies on breakaways (74) and sprinting (144), little research has extensively examined these tactics and their influence on the demands of cycling.

Grand cycling tours (*Tour de France*, *Giro d'Italia* and *Vuelta a España*) are perhaps the most popular and demanding races in the professional road cycling calendar. Since the first tour in France in 1903, these grand tours have been established as some of the most predacious sporting events in history. These races are performed over 21 days, with minimal recovery time between stages (only 1 - 2 days of complete rest). Historically, the *Tour de France* covered over 5000 km, however, this and the average time for completion has reduced over recent years (145). Modern day tours consist of more than 200 cyclists at the beginning of the race. The cyclists cover around 3650 km in an average time of 92 ± 6 h (46, 146). Competing in a grand tour is similar to a multi-day stage race. These tours have several teams (e.g. the 2016 *Tour de France* started with 219 riders from 22 teams) and each team may have different objectives. For example, objectives may include sprint, mountain and general classification classifications, high podium finishes or stage wins. With multiple objectives, grand tour events are extremely complex with many tactical decisions influencing the race outcomes. To date, the majority of research that has examined the workload demands of professional male road cyclists during a grand tour event has quantified exercise intensity using heart rate (11-14, 56, 102, 109). The majority of these studies have found that topography influences exercise intensity (11-13). For example, Padilla et al. (102) examined the heart rate of sixteen world-class professional male cyclists during grand tours. In this study, the average percentage HR_{max} was 61 ± 5%, 58 ± 6% and 51 ± 7% in high-mountain, semi-mountain and flat stages, respectively. With the advancement in power meter technology, more recent studies have provided more detailed description of power output in professional cyclists during grand tours (15, 18). For example, Vogt et al. (15) described the power output of fifteen professional road cyclists across three topography categories (flat, semi-mountainous and mountainous) from the 2005 *Tour de France*. They found that relative power output was significantly lower on flat stages compared with semi-mountainous and mountainous stages (3.1 ± 03, 3.3 ± 0.3 and 3.3 ± 0.2 $W \cdot kg^{-1}$ respectively). Additionally, cadence was significantly lower on mountainous stages, compared with flat and semi-mountainous stages (81, 87 and 86 rpm respectively). However, the influence of topography on power output and self-selected cadence during professional road cycling is not well established. Such information is important given the range of race characteristics and various objectives within such events.

In conclusion, professional road cyclists compete in a variety of road racing types (time-trial, single-day, multi-stage and grand tour). These events have distinct characteristics, are extremely dynamic, and may have multiple objectives within a single event. As a result, the demands of each of these events differs drastically. The physiological requirements of a cyclist change depending on the event or task of an individual cyclist (described in section 2.3.3) (14). Furthermore, external demands appear to be heavily influenced by external variables such as stage topography.

2.3.2 Topography categories

The influence of topography is one of the most significant challenges facing professional road cyclists. Within the literature, cycling stages and events that have been categorised based on topography are typically defined as flat, semi-mountainous or mountainous stages (Figure 2.1). Several factors are taken into consideration when classifying these stages, including the length and grade of the climb and where the climb occurs during a race or tour. These climbs or mountain passes are classified by number categories (1 to 4) based upon their difficulty. This section introduces the current literature examining flat, semi-mountainous and mountainous stages.

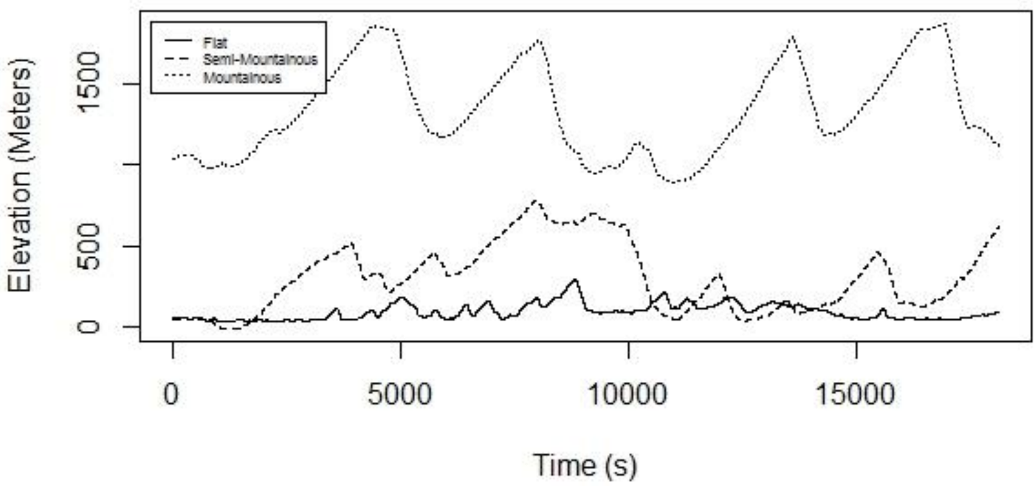

Figure 2.1: An example of three *Tour de France* stage types based on topography categories.

Flat races and stages are typically over 200 km and performed over durations of approximately 4 to 5 h (146). During flat stages from a grand tour, Fernandez-Garcia et al.

(11) calculated that approximately 93 min of cycling time were spent above 70% of $\dot{V}O_{2max}$. Air resistance is the most dominant resistive force the cyclists experience during flat stages (147). As a result, flat stages are typically the fastest with average velocities of around 45 $km{\cdot}h^{-1}$ reported for flat grand tour stages, compared with around 20 $km{\cdot}h^{-1}$ during uphill cycling in mountainous grand tour stages (146). At higher speeds greater power output is required to overcome air resistance. To reduce the impact of air resistance, riders will draft behind others within the race. Such drafting has a drastic influence on energy demands during cycling. Indeed, a reduction in $\dot{V}O_2$ of approximately 40% when riding in a large group has been reported between 21-40 $km{\cdot}h^{-1}$ (148). As a result, cycling teams will often deliberately shelter specific team members depending on an individual's role within the team (described in more detail in section 2.3.3). The ability of riders to position themselves in various sections within a peloton and at different stages of a race, results in varying energy demands, even during flat road cycling events. Indeed, power output has been shown to vary drastically during flat stages of road cycling events (8). While several studies have attempted to replicate such events in laboratory settings (23, 137, 149, 150), few studies have attempted to describe their stochastic nature. Further work is needed to describe the power output characteristics of road racing before replicating studies in the laboratory.

Semi-mountainous or mountainous stages are typically over 200 km and performed over durations of approximately 5 to 6 h (146). These stages are extremely important in the overall outcomes of grand tours. Indeed, performance in these stages in the 2001 *Tour de France* has been shown to be correlated ($r = 0.94$) to total race time (151). These stages are extremely demanding and contain multiple mountain passes, which typically range between 5-10 km at grades of 3-15% (146). Semi-mountainous and mountainous stages also involve long constant periods of uphill cycling (13, 102). During such cycling a significant energy contribution is required to overcome gravity. As a result, success during such events requires athletes to have high aerobic capacities and very high power to mass ratios ($W \cdot kg^{-1}$).

During the mountainous stages of a road cycling race, altitude increases result in a reduction in the fraction of inspired oxygen and increased time on steeper road gradients. While there has been a significant amount of research demonstrating the influence of cycling performance at altitude (152), few studies have looked at data from actual professional road cycling races. Only one study has investigated the impact of altitude on power output during a multi-stage race (62). This study demonstrated an 11.7% reduction in peak power output and maximal mean power (MMP) between 5 and 600 s while racing at greater than 3000 m compared with sea level. Overall, an approximately 6% reduction in performance capacity per 1000 m above sea level was observed (62). Research has similarly demonstrated the influence of an increased road gradient on cycling performance (37-39, 153, 154). However, little is known about the influence of road gradient from actual professional road cycling races other than Padilla et al. (12) who discussed the demands of grand tour ascents of differing length and gradient. The authors concluded that mountain passes were highly demanding and that a cyclist's intensity was not only related to the difficulty of accent but also their position within a stage. During uphill cycling the task demands change with a lower speed and freely chosen cadences (155). Under those circumstances, more time is put through the pedal with the most difference occurring between 45° and 135° of the crank torque profile during maximal aerobic power (156). With a decrease in performance capabilities at altitude and on increased road gradients, greater attention to detail in the performance analysis of these stages is warranted given these stages have a high correlation with the overall success of a professional road cycling team.

In conclusion, there are three main stage types: flat, semi-mountainous and mountainous. The definition of each of these stage types is based on their individual topography (excluding time trial). Before each race, riders should be aware of the stage dynamics and where and when to expect difficult sections.

2.3.3 Rider specialities

Each of the UCI (Union Cycliste Internationale) professional cycling teams comprises of approximately 24 riders (1). Given the complexity of professional road cycling, athletes are often categorised into separate speciality groups, depending upon their specific strengths, physiology and role within a team. The classification of these groups has varied within the literature. Padilla et al. (157) described the classifications as uphill riders, flat terrain riders, all terrain riders, time trial specialists and sprinters. Other studies have described rider specialities in terms of their skill (26) or role (15) within the team. These groups typically include the general classification rider (or team leader), domestiques (or team helper (15)), climbers, and sprinters. Additionally, categories based upon age have appeared within the literature and include masters (Over 35) (158), amateurs (Under 23) (43, 159) and juniors (Under 19) (160). This section introduces the current literature examining general classification, domestiques, climbers and sprinters.

The general classification rider is a cyclist who specialises in multi-day stage or grand tour events. The most important objective for this rider is to be placed as high as possible in the general classification. To do this, the rider must have the lowest time over multiple days. Within any one team there are a limited number of general classification riders, with teams usually starting a multi-day tours with a single cyclist as the general classification rider. The physiological characteristic of general classification riders have been reported as an extremely high aerobic capacity ($\dot{V}O_{2max} > 85$ mL·kg^{-1}·min^{-1} (44), peak power output at the end of aerobic test > 525 (161) and 572 W (130), and gross efficiency of > 23% (161)). To the author's knowledge, only one published case study has described the workloads of a general classification rider who reported an increase in weekly total duration (from 10.1 h to 18.1 h) and training load (from 3061 arbitrary unit (AU) to 5608 AU) during a six year period. While other data do exist on a general classification rider (162), these data were collected during a period of doping and are, therefore, questionable (163). The limited research on general classification riders is likely due to the reluctance of professional road cycling teams to publish power output data and the very small population of these riders. Therefore, more research is required into the physiological characteristics and workloads of these general classification riders.

It is the role of the domestiques to protect the general classification rider as much as possible from any additional workload, ensuring that the general classification rider is still in good condition towards the end of each stage. No known study has examined the specific physiological characteristics or workloads of domestiques riders. While Vogt et al. (15) do mention a 'team helper' and climber categories, no analysis was conducted between each. Future research is warranted into the characteristics and workload demands on the domestique riders in this role.

Climbers are cyclists who perform well during mountainous stages. They excel on specific topography type and single stages rather than a total multi-stage race win. Climbers will contest for a stage victory in the mountains and attack when the gradient increases. Professional male climbers have a lower body mass (~ 62 ± 4 kg) compared with flat (~ 76 ± 3 kg) and all-terrain (~ 68 ± 3 kg) riders (1). Despite lower absolute peak aerobic power in climbers (404 ± 34 W) compared with flat (461 ± 39 W) an all-terrain (432 ± 27 W) riders, a lower body mass means that climbers typically have a greater power to mass ratio (6.5 ± 0.3 $W \cdot kg^{-1}$) and relative $\dot{V}O_{2max}$ (80.9 ± 3.9 $mL \cdot kg^{-1} \cdot min^{-1}$) compared with flat (6.0

± 0.3 W·kg^{-1}, 74.4 ± 3.0 mL·kg^{-1}·min^{-1}) and all-terrain (6.4 ± 0.2 W·kg^{-1}, 78.9 ± 1.9 mL·kg^{-1}·min^{-1}) riders (1). Overall, it has been suggested that the minimum workload requirements for successful professional male climbers are a power to mass ratio of greater than 6 W·kg^{-1} held for at least 40 min (56, 157).

Sprinters will contest for stage victory and will only attack in the very final stages of a race. Sprinters are protected by fellow teammates leading into the finish which is necessary for a successful sprint performance (164). The physiological demands of under 23 (164) and professional (165) male road sprint cyclists during and leading into the sprint has been well defined. During the final sprint, professional male sprint cyclists have, at sprint peak, demonstrated absolute power output values of 1248 W and relative power output values of 17.4 W·kg^{-1}, cadence of 114 rpm, and peak speeds of 66 km·h^{-1} (165). This final maximal sprint is influenced by pedal rate, muscle size, fibre type and how fatigued the rider is leading into the sprint (166). The whole duration of the final sprint demonstrated absolute power values of 1020 W and relative values 14.2 W·kg^{-1}, cadence of 110 rpm and peak speeds of 63.9 km·kg^{-1} (165).

Menaspà et al. (144, 159, 165, 167) have extensively examined the external workload demands leading into the final sprint. These authors found that average power output increased by 10, 5 and 1 min leading into the sprint (332 ± 23, 376 ± 28 and 450 ± 40 W, respectively). It is plausible that the set average time periods have caused these results. A more statistical time series based approach would be more applicable where the researcher does not dictate the length of each time period (168). This would not only be useful during a final sprint but also throughout a stage. While the sprint is an extremely important aspect of many races, little information is available regarding other maximal efforts which may be observed during professional cycling events.

In conclusion, several different rider specialities exist resulting in a variety of different roles within a professional cycling team. There is a substantial lack of understanding on how the workload demands differ between the roles (14). Future research should begin to investigate the different workload demands between rider specialities.

2.4 Methods to Analyse Power Output in Professional Road Cycling

While numerous external variables can be measured, power output measured using a power meter provides the most useful information in quantifying external workload from professional road cyclists (30). This section introduces existing methods used to analyse power output including data reduction and power-duration curves as well as suggesting a new time series based method entitled ‘changepoint’ analysis.

2.4.1 Data reduction methods

Data from a single ride can result in a significant amount of data points provided by a number of different variables (i.e. altitude, gradient, cadence, power output, speed, heart rate and temperature). Previous research using professional road cyclists have reduced large scale heart rate, cadence, distance and speed data sets into training/race ‘bins’ or ‘zones’, using histograms for graphical analysis (12-14, 101, 102). This section describes the research into training or racing power output zones in professional road cyclists and procedures in which these zones have been developed.

2.4.2 Time in training zones (power binning)

Power output distribution can be described within a single stage, multi-stage, within-season and between seasons using time spent in designated data bins or zones. Data bins are generated using percentage total time spent within a power band. Ebert et al. (10) used four power (0-100 W, 100-300 W, 300-500 W and > 500 W) and power/mass (0-2 $W \cdot kg^{-1}$, 2-5 $W \cdot kg^{-1}$, 5-8 $W \cdot kg^{-1}$ and >8 $W \cdot kg^{-1}$) bins when analysing an elite men’s multi-stage race and again four power bins (0-1.9 $W \cdot kg^{-1}$, 2.0-4.9 $W \cdot kg^{-1}$, 5.0-7.9 $W \cdot kg^{-1}$ and >8.0 $W \cdot kg^{-1}$) when analysing women’s World Cup road cycling events (9). Using relative power bands provides a better comparison when comparing demands as a rider’s body mass has been demonstrated to be different between riders of differing speciality (1, 23, 41-43). In the literature, an alternative to power output bins is to use functional threshold power (FTP). Functional threshold power is the maximum average power a cyclist can hold for one hour and can be measured in the field using a validated 20 min test (169). In a longitudinal study of power output in elite cyclists (170), time in exercise intensity zones was related to FTP bins (< 50%FTP, 50-70%FTP, 71-85%FTP, 86-105%FTP, 106-125%FTP,126-170%FTP & > 170%FTP). Ultimately, the objective of data bins is to break down large stochastic data sets and to simplify complex data. Although power binning large data sets, variations in the power output are lost in analysis and may lose important characteristics such as an attack or breakaway. Also, power zones for each rider are individualised (i.e. each rider has their own physiological characteristics). Therefore, intra-subject variability should be considered when analysing multiple riders, however, this is difficult as analysis is based upon physiological limitations. This requires laboratory testing for each cyclist which is difficult, expensive and time consuming.

2.4.3 Exposure variation analysis

Exposure variation analysis is a more detailed way of analysing binned data which described not only the distribution of power output bands but also the acute time spent in each time band. Exposure variation analysis first used by Mathiassen & Winkel (171) is designed to reduce the activity of a stochastic dataset and has now been applied to some stochastic models in cycling (137, 138, 165, 172). Results using exposure variation analysis have been reported using cycling power output data in two studies (8, 172) and pacing strategy in a single triathlon study (173). During different cycling events, Abbiss et al. (8) found meaningful variations in the results of each event. The authors concluded that the analysis might be a useful tool for quantifying changes in the amplitude and time distribution of power output. Thereafter, Peiffer & Abbiss (138) and Menaspá et al. (165)

used exposure variation analysis to investigate power output distribution in different environmental conditions and in professional road cycling sprint demands respectively. The limitation with exposure variation analysis is that it requires the analyser to select the scale of amplitude and time bins, similar to power band distribution. Consequently, Passfield et al. (172) used a data-reduction method named Shannon's entropy to reduce the subjectivity of data binning choices when using exposure variation analysis. Subsequently, data binning choices available to the experimenter increases the room for error in data interpretation. For example, one investigator may use five data binning choices whereas another may use ten. This makes it difficult to compare results and if inconsistent over time will result in comparison error. There is also little research about transferring exposure variation analysis output into clear practical feedback for training interventions. Realising the gap in the literature, more research is needed into the practical use of exposure variation analysis.

2.4.4 Power-Duration curves

Much of this research described has simply been characterising the time spent within various workload intensities or the average power output/heart rate zones during different stages of a race. While these analyses can provide the percentage time in exercise intensity zones they do not give any indication of time at maximal capacities. Within the literature, CP and MMP are two popular power-duration analyses which aim to quantify the maximal capacities of professional road cyclists. This section describes these two methods and how they can be used to analyse power output.

2.4.5 Critical power model

In 1925, A.V Hill (174) first noted the curvilinear relationship between work rate and performance time. It was not until the 1960's that Monod & Scherrer (175) during lifting exercise, developed a mathematical formula for the curvilinear relationship originally observed by Hill. The model, defined as CP was extended during the 1980's (176, 177) using whole body exercise with humans exercising to exhaustion at different work rates. The concept is now very popular in modelling across a range of endurance performance disciplines. A simple two-parameter model, CP is defined as the hyperbolic relationship between power (P) and time (t), mathematically represented where CP is critical power and AWC is anaerobic capacity.

$$(P - CP)t = AWC$$

Practically, the CP model provides an easy to use mathematical model in analysing power data, in doing so, quantifying specific physiological zones, but the CP model does come with several inaccuracies and assumptions (178). The CP model assumes that there are three energy producing pathways including high-energy compounds, glycolysis and oxidative phosphorylation. The model also assumes that power output declines below the CP given enough time. However, this time varies between 2 and 30 min but, can last up to 60 min certain individuals (179). Furthermore, there is a finite limit in *W'* depending on maximum power and exhaustion can occur even though *W'* is not completely depleted (180). Moreover, the two-parameter CP model tends to overestimate the CP and AWC. Therefore, modifications to the CP model have been developed into a three-parameter model (181) to address these limitations, mathematically represented where *k* is asymptote and assumes a negative value.

$$t = \frac{AWC}{(P - CP)} + k, (k < 0)$$

Cycling power output is stochastic and highly intermittent in nature with previously described CP models failing to take this fluctuation into account. CP was first applied to intermittent exercise by Morton and Billat (182) in runners and implemented to intermittent cycling exercise by Chidnok et al. (183). The intermittent CP model proposed by Morton and Billat (182) is mathematically represented where t is the total time, P_w and P_t are equal to the work and rest interval power, and T_w and T_r are equal to work and rest interval time.

$$t = n(t_w + t_r) + W' - n[P_w - CP)t_w - (CP - P_r)t_r]/(P_w - CP)$$

CP is an important fatigue threshold in exercise physiology (28, 29). The hyperbolic power-duration curve can be broken down and defined as severe, heavy and moderate exercise based upon exercise intensity (29). The point of CP defines the boundary between heavy and severe exercise intensity domains. Exercise below CP can be maintained whereas exercise above CP results in an exponential rise in oxygen uptake leading to exhaustion (28). Theoretically, CP represents a power output which can be maintained using aerobic metabolism and has been shown to be related to cycling time trial performance (184).

In professional road cycling, exercise physiologists can use CP to prescribe and analyse exercise performance. To do this, an accurate measurement of CP is required. Traditionally, CP can be measured using multiple exhaustive bouts of exercise on separate days (185), however, recent studies have proposed a single 3 min all-out test (32) and field-based tests (33, 34). Using an all-out 3 min test in the laboratory, Vanhatalo et al. (32) suggested that the final 30 s power output represents CP and can be used to track training-induced alterations (31). Alternatively, the retrospective analysis of professional road cycling power meter data can be analysed to obtain a CP estimation. Karsten et al. (34) reported a high reliability and validity in estimated CP using 12, 7 and 3 min MMP values. While these options provide a retrospective analysis, our understanding of how accurate these models are is limited. Indeed, both Triska et al. (186) observed a 34% decrease when determining CP in the field (road cycling) and Dekerle et al. (187) observed a 14% decrease in CP when cycling at altitude. In that case, an acknowledgement in the variation of retrospective analysis in power output from alternative altitudes is required. Failure to not adjust CP measurement would result in a high level of error to prescribed exercise and post-exercise performance analysis.

2.4.6 W' balance model (W'$_{bal}$)

In establishing the CP curve, exercise completed above the curve is termed anaerobic work capacity (AWC). Exercise above CP expands AWC whereas below reconstructed AWC (45, 183, 188-190). Chidnock et al. (183) found that exercise tolerance is improved during recovery intervals in proportion to the restoration of finite AWC, if exercise is performed below CP. The restoration of finite AWC is directly related to the intensity and duration of the recovery interval. The mechanisms determining AWC remain uncertain, however, in healthy populations, it has been proposed that AWC is associated with intramuscular energy store depletion (191-194) and metabolite accumulation (190, 191, 195, 196). As a result, alterations in the breadth of the server domain (197, 198), the volume of oxygen uptake slow component kinetics (199) and the development of fatigue (198) all occur.

Integrating the mechanisms of CP and AWC, Skiba et al. (200) recently proposed a simplified dynamic model for the real-time monitoring of intermittent exercise using the discharge and recharge of AWC kinetics during intermittent exercise as observed by Chidnock et al. (183). The equation by Skiba et al. (200) for AWC remaining at any given time during an exercise session is mathematically represented as W'_{bal} where AWC equals the subject's know AWC as calculated using a two-parameter CP model, W'_{exp} is equal to expanded AWC,$(t - u)$ is equal to the time in seconds between segments of exercise session that result in depletion of AWC and $t_{w'}$, is the time constant of the reconstitution of the W'.

$$W'_{bal} = AWC - \int_0^t (W'_{exp})(e^{-(t-u)/t_{w'}})$$

The *W'_{bal}* model proposed by Skiba et al. (200) is of highly practical significance for the retrospective analysis of power output and has been validated in the field (201) in well-trained triathletes. The model has also recently remained valid during hypoxic conditions (202). No difference in *W'_{bal}* balance estimates was observed between normoxic and hypoxic conditions. However, a correction factor for CP will need to be considered for successful *W'_{bal}* balance. Otherwise, *W'_{bal}* can be under or overestimated depending on condition. Indeed, Valli et al. (203) recently demonstrated a 45% reduction in AWC at high altitude (5050 m, $F_IO_2 \sim 0.11$) compared with sea level cycling exercise. Future work is required to determine the practical application of *W'_{bal}* in professional road cyclists training and racing.

2.4.7 Maximal mean and record power curves

To better understand the physiological requirement of professional road cycling events, researchers, coaches and sports scientists have recently begun to quantify the acute time spent over a set duration using a hyperbolic power curve analysis called the maximal mean power (MMP) curve. The MMP is based upon the power-duration relationship introduced in section 2.4.5. The field-based method determines the hyperbolic relationship between work capacity and time. Therefore, MMP may be able to provide an indication on the physiological capacities (i.e. CP) of professional road cyclists in the field. Quod et al. (27) have shown that a cyclist's MMP curve produced over a range of durations (5, 15, 30, 60, 240 and 600 s) within the laboratory, accurately reflects their maximal capacity and MMP curve from analysis of competition data. This study shows that data in the field might be beneficial in quantifying maximal power producing capabilities of athletes.

Determining the MMP curve of cyclists over various periods of time allows for better quantification of the physiological demands during professional road cycling. Pinot and

Grappe (26) performed an investigation into monitoring the MMP curve (1, 5, 30, 60s, 5, 10, 20, 30, 45, 60, 120, 180 and 240 min) over a 10 month period in seventeen male road cyclists (9 professional and 8 elite). The authors demonstrated a hyperbolic relationship between recorded power output and the time durations from a MMP curve. The authors also noted that alternative rider specialities showed specific changes to the MMP curve although participant numbers were low (sprinters n = 5, climbers n = 7 and flat n = 5). Specifically, power output was greatest in sprinters in between 1-5 s (20.2 $W \cdot kg^{-1}$) whereas, climbers presented their highest recorded power output between 30 s and 60 min (6.8 $W \cdot kg^{-1}$). Climbers and time trial specialists also presented high power outputs in zone 1 (1 to 4 hrs of moderate intensity) between 120 and 240 min (4.1 and 4.0 $W \cdot kg^{-1}$ respectively). These results suggest the MMP curve could be a useful external load monitoring tool showing physiological changes over time (25) yet, there are few studies which have examined this in professional male road cyclists.

Continuous analysis of MMP curves has been recorded during a professional road cycling competitive season (25). The highest power values recorded during the season were described as a record power profile. While Pinot and Grappe uses 'record power profile' (204), the term 'maximal mean power' (MMP) will be used throughout this thesis for the same value. Recently, the MMP curve was used as a power tool for the assessment of longitudinal performance in a single professional male road cyclist who has twice finished in the top ten of a grand tour event (44). The study monitored the cyclist over a six-year period between the ages of 18 and 23 y. The authors concluded that MMP was able to illuminate the cyclist's maturation for physical potential as a top 10 grand tour cyclist. The study highlights the use of the MMP and the development of MMP for longitudinal monitoring of power data rather than bulk training bands. For example, figure 2.2 demonstrates two MMP curves, pre-competitive and during the competitive season. The curve demonstrates adjustment depending on what time of the season it is recorded. Unfortunately, few studies have been carried out on monitoring the MMP curve in professional male road cyclists and, therefore, needs to be addressed.

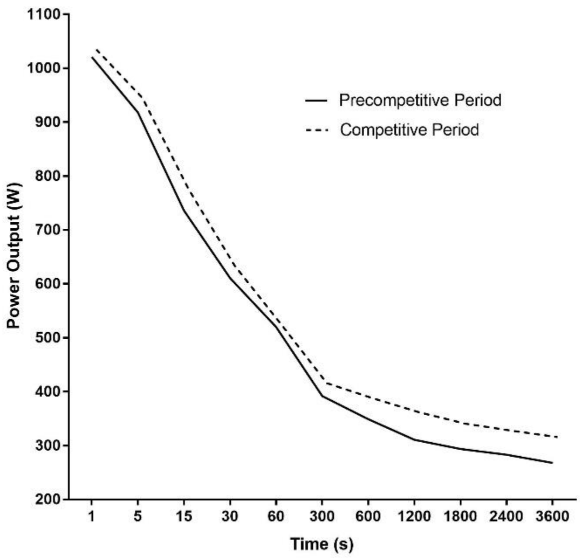

Figure 2.2: An example of expected change in a cyclist’s MMP curve between pre-competitive and competitive periods.

MMP may be beneficial for talent identification and monitoring training and racing adaptations, performance, and fatigue in professional cyclists. This being said, only a few studies have examined how various external factors (i.e. topography, rider speciality, or race dynamics) may influence MMP (15, 25). For example, Quod et al. (27) calculated MMP from multiple races (n = 10) of varying duration (1 to 10 days), distance, (80 to 180 km), topography (flat, rolling or mountainous) and race format (criterium, circuit and point-to-point races). Therefore, it is not clear if MMP differs when calculated for different factors.

In conclusion, direct power output provides a reliable measurement of external workload. While direct power output figures from professional male road cyclists have been published, future research is warranted into the effect of varying the external workload on the MMP curve. More research is also required into the within-season variation of the MMP curve. Also, research into the season to season variation is required to confirm the MMP method as a valid way to assess external workload over time.

2.4.8 Time series data (changepoint)

Power output is a sequence of multiple data points over a chronological period and can be described as time series data. Current methods of analysing power output over time are limited in locating trends within the single and multiple data files. The ability to pinpoint certain segments of time where power output is increased or decreased between a mean could be a valuable way to assess power output data without using a reduction method. Within a time series or sequence set of data, the ability to locate multiple statistical changes can be achieved using changepoint analysis (168). Sports scientists and cycling coaches can determine how detailed they required analysis to be using either single or multiple changepoints. Unlike time in training zones or mathematical models, changepoint provides a fast an easy method in reducing the stochastic nature of a single stage.

In this example (Figure 2.3), a single stage has been analysed. However, changepoint has implications for the analyses of periodic longitudinal data. To date, no study has investigated the use of changepoint analysis in sports science and more specifically, cycling power output. Future research is warranted on the practical application of this analysis and its integration into cycling power output data analysis.

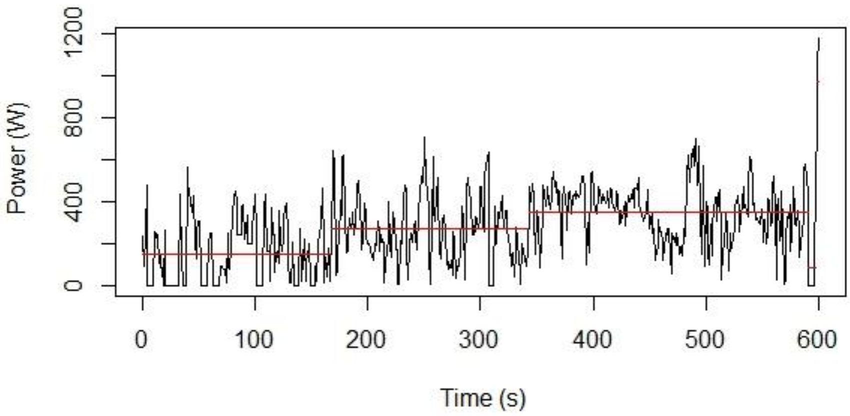

Figure 2.3: An example of segments from a changepoint analysis in a single professional road cyclist's power output over 600 s.

2.5 Summary and Conclusions

Professional road cycling can be categorised into several subsections including competition types (section 2.3.1), topography categories (section 2.3.2) and rider specialities (section 2.3.3). Our understanding on quantifying the influence of competition types, topography categories and rider specialities (Table 2.1) from endurance cycling performance in professional male road cyclists is currently limited. In this literature review, there appears to be no shortage of methods in which cycling power output data can be analysed (section 2.4). However, there appears to be a gap (e.g. first black box) in our understanding of how external factors such as topography and road gradient or rider speciality influence the performance analysis (Figure 2.4). It is, therefore, essential that existing methods are tested using these external factors and new techniques are developed if appropriate (e.g. second black box).

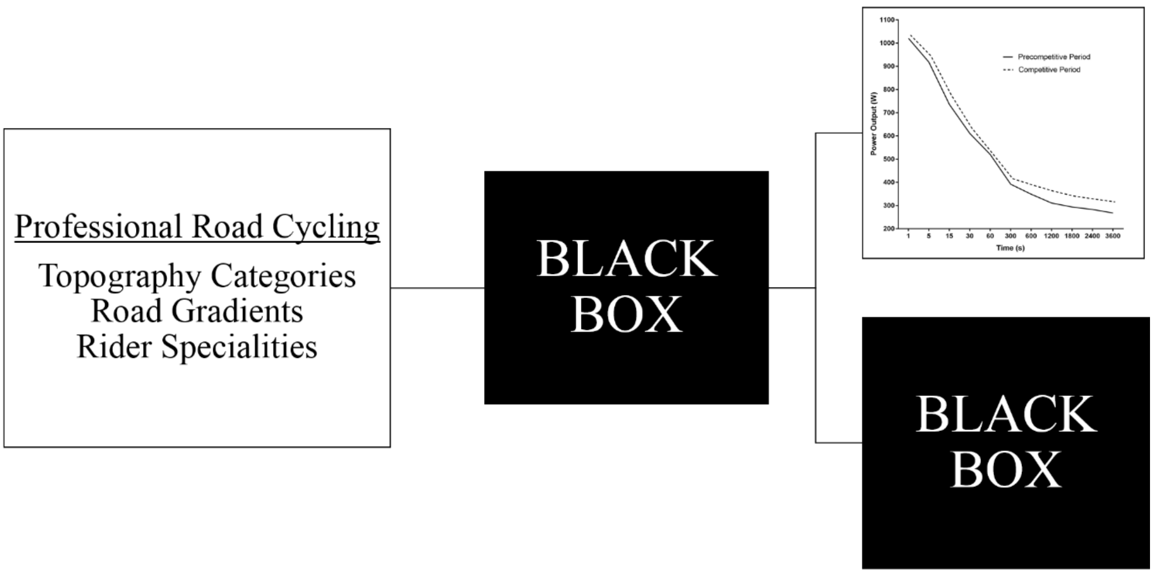

Figure 2.4: A schematic on the gap between different external factors and performance analysis techniques covered in this literature review.

3 CHAPTER THREE

EXAMINING THE DISTRIBUTION OF MAXIMAL POWER OUTPUT EFFORTS AND THE USE OF CHANGEPOINT ANALYSIS IN PROFESSIONAL ROAD CYCLISTS

3.1 Abstract

Introduction: Power output during road cycling is stochastic with multiple maximal efforts occurring throughout a stage race. ***Purpose:*** The purpose of this study was to calculate the frequency distribution of maximal power output (PO_{peak}) values during road cycling events over different topography categories and analyse the power output 600 s prior to PO_{peak} using a new time series analysis. ***Methods:*** Fifty-seven stages from seven professional male road cyclists were analysed. Power output was recorded using SRM power meters. Stages were classified as either flat (n = 37), semi-mountainous (n = 8) or mountainous (n = 12) based upon total uphill riding time and the total elevation gain. PO_{peak} was determined as the highest single absolute power output value recorded for each stage. The frequency distribution of PO_{peak} values was calculated into five percentage of race time bands (0-20, 20-40, 40-60, 60-80 and 80-100% of race time). The 600 s prior to PO_{peak} was analysed using a time series based analysis: changepoint. Changepoint estimated the four largest statistical changes in power output to find four distinct segments. Power output and time were compared between segments. ***Results:*** A greater frequency of PO_{peak} values (54%) occurred during flat stages in the final 80 to 100% of race time compared with the previous 0 to 80% race time. Power output was lower (P <0.05) in segment four compared with PO_{peak} in all topography categories (flat: 235 vs. 823 W, semi-mountainous: 157 vs. 886 W and mountainous: 171 vs. 656 W). ***Conclusion:*** PO_{peak} values were alternatively distributed depending on the topography category. Changepoint demonstrated its ability to reduce stochastic data while maintaining meaningful information.

Keywords: *Time-Series, Stochastic, Topography, Performance Analysis.*

3.2 Introduction

During professional road cycling races, riders conduct periods of maximal exercise. These are so-called 'matches' or 'peak efforts' (PO_{peak}) and place a high metabolic demand on the rider, often within a short period of time resulting in a sustained reduction in anaerobic energy sources. Prior to establishing a breakaway, Abbiss et al. (74) demonstrated that numerous short-duration (~ 5-15 s), high-intensity (~ 9.5-14 $W \cdot kg^{-1}$) efforts are produced. It is likely that the distribution of such efforts is heavily influenced by serval factors including topography, gradient, wind or race dynamics.

These PO_{peak} efforts increase the stochastic nature of power output and the complexity of analysing such data. Several studies have attempted to describe (8, 205) or replicate (167, 206) the stochastic nature of cycling. Tucker et al. (205) found continuous oscillations in power output during a 20 km self-paced time trial. While Abbiss et al. (8) used exposure variation analysis in illustrating variations in power output during five- and single-day professional road cycling events. Studies which have tried to replicate the stochastic nature in the laboratory have used efforts interspersed constantly throughout a trial. To replicate, Schabort et al. (206) used five 1 km efforts (10, 32, 52, 72 and 99 km) and five 4 km efforts (20, 40, 60 and 80 km) during a 100 km time trial. In shorter efforts, Menaspà et al. (167) replicated stochastic power output using a variable and a non-variable condition for 600 s prior to a maximal sprint.

Changepoint analysis is an analytical method developed to analyse time series data. Briefly, changepoint estimates the point at which the statistical properties of a sequence observe change. These points are split into segments for further analysis. To the author's knowledge, changepoint method has not been used within the discipline of sport and exercise sciences. However, recent examples in other disciplines include its use in oceanography (207) to quantify wave height during storm events across the Gulf of Mexico between 1900 to 2005 and in medical imaging (208) to detect changes in brain blood flow using functional magnetic resistance imaging. An advantage of changepoint is that the resulting output detects changes in the stochastic data which are not necessarily easy to detect by an experimenter. For example, in cycling exercise Menaspà et al. (159) analysed power output for 600 s prior to a sprint effort. The experimenters selected to analyse average power output segments of 600 s, 300 s and 60 s prior to sprint performance. Changepoint analysis may provide a more accurate alternative to arbitrarily selecting segments. It is, therefore, possible that analysing the changepoint segments from power output data in cycling exercise may provide a more accurate measurement.

Knowledge of where these PO_{peak} efforts occur during a stage race and the exercise intensity prior to that point will aid in our understanding of the race dynamics of professional road cycling. The primary purpose of this study was to describe the frequency distribution of PO_{peak} values from different stage topography categories (flat, semi-mountainous and mountainous). We hypothesised that a higher frequency of PO_{peak} values would occur during the final section (> 80% of total race duration) of flat stage races as exercise intensity increases towards the finish. It was also hypothesised that in semi-mountainous and mountainous stages, the frequency of PO_{peak} values will be more evenly distributed across the stage races as few sprint finishes are produced. The secondary aim of this study was to use a novel changepoint method to analyse the distribution in power output 600 s prior to PO_{peak} efforts from different stage topography categories (flat, semi-mountainous and mountainous). We hypothesised that power output 600 s prior to PO_{peak} will progressively increase during flat compared to semi-mountainous and mountainous stages due to the demands of a final sprint towards the finish. A more even distribution will be observed in power output prior to PO_{peak} in semi-mountainous and mountainous stages.

3.3 Methods

3.3.1 Participants

Seven professional male road cyclists (mean ± SD: age 29.5 ± 2.8 y, mass 69.7 ± 5.5 kg, height 182 ± 5 cm) participated in this study and were all members of a single professional cycling team. The cyclists were classified as level 5 based on the study of De Pauw et al. (209). All participants gave their written informed consent. The study was approved by the Edith Cowan University Human Ethics Research Committee.

3.3.2 Data collection and analysis

In total, fifty-seven stages from multi-stage road races in four professional road cycling tours between 2011 and 2013 (*Volta ao Algarve* 2011 (*n* = 10 stages), *Internationale Osterreich Rundfahrt* 2011 (*n* = 19 stages), *Tour de Belgique* 2012 (*n* = 8 stages) and *Criterium du Dauphine* 2013 (*n* = 20 stages)) ranging from 4 to 7 days were analysed. Three riders were analysed in each event, therefore, not all seven professional road cyclists competed in the same events. Multi-stage road races were broken down into stage type for comparative analysis based upon the stage topography (flat *n* = 37, semi-mountainous *n* = 8, mountainous *n* = 12). Stage topography was classified using previously published research (102) as well as updating the classification criteria using the total elevation gain (TEG) provided by the power meter during each stage. TEG is calculated from a barometric altimeter. The SRM power meter has been demonstrated to provide accurate and reliable measurement of TEG (210), however, weather conditions causing a reduction in barometric pressure may reduce accuracy (211). Specifically, flat stages were classified stages with a total uphill riding distance of less than 13 km and TEG of less than 800 m. Semi-mountainous stages were classified stages with a total uphill riding distance between 13 and 35 km and a TEG between 800 and 2000 m. Mountainous stages were classified as a total uphill riding distance of more than 35 km and a TEG of more than 2000 m.

Power output and altitude were recorded using SRM (SRM Trainingsystems, Schoberer Rad Messtechink, Julich, Germany) power meters mounted on the participant's bikes during each stage. The validity and reliability of the SRM devices have been previously reported (45, 51). All power meters were statically calibrated at the beginning of each season and re-calibrated if battery replacement occurred during each season. The SRM PowerControl was set to perform the zero-offset for every race automatically. Race files were uploaded to a computer. Race data was then stored and analysed using Golden Cheetah (v.3.1.0) and Microsoft Excel 2012 (Microsoft, USA). Power values were recorded at a frequency of 1Hz. The single highest power output value recorded from each stage race was classified as the stage's PO_{peak} value.

3.3.3 Changepoint detection

Power output 600 s prior to stage PO_{peak} was modelled using a software package entitled 'c*hangepoint'* (168) with function '*cpt.mean*' in the R statistical programme (212). All models were instructed to estimate the 'four' greatest statistical changes within the 600 s before PO_{peak}. Specifically, penalty (statistical change) was based upon AIC (Akaike Information Criteria) at a penalty value of 0.05 (α = 0.05). The "BinSeg" method was adopted were by the maximum number of segments were searched for (Q = 4). In this case, the maximum number of segments was 4 (+1). The most common approach in the literature (168, 213) which identifies multiple changepoints was used:

$$\sum_{i=0}^{m+1} [C(y(t_{i-1}+1):t_i)] + \beta f(m)$$

where C is the cost function of each segment, βf is the penalty guard against overfitting, y is the ordered sequence of data, t is he position of changepoints and m is the number of changepoints.

3.3.4 Statistical analysis

The frequency distribution of PO_{peak} values were calculated using the R statistical programme (212). The number of times PO_{peak} values occurred was calculated on the frequency distribution between 0 to 20, 20 to 40, 40 to 60, 60 to 80 and 80 to 100% of total stage time. Frequencies were compared as a percentage of raw PO_{peak} values. For each changepoint segment, power output and time were compared between corresponding segments left-to-right (1 - 2, 2 - 3, 3 - 4 and 4 - PO_{peak}) in each topography category using a one-way repeated measure ANOVA. Where significant effect was observed, Bonferroni's multiple comparisons post-hoc test was applied. The 95% confidence intervals [95% CI] were also calculated for the power output and time of each segment. Segment values were extracted using *'summary'* and *'coef'* functions after changepoint analysis (168). For all variables, statistical significance was accepted at P <0.05.

3.4 Results

The percentage of frequency distributions between topography categories are shown in figure 3.1. Greater frequency of PO_{peak} values (54%) occurred during flat stages in the final 80 to 100% of race time compared with previous 0 to 80% race time (Figure 3.1). Figure 3.2 demonstrates an example of changepoint analysis for each topography category. Power output and time length for each changepoint segment is presented in table 3.1. Power output was lower ($P<0.05$) in segment four compared with PO_{peak} in all topography categories (Table 3.1).

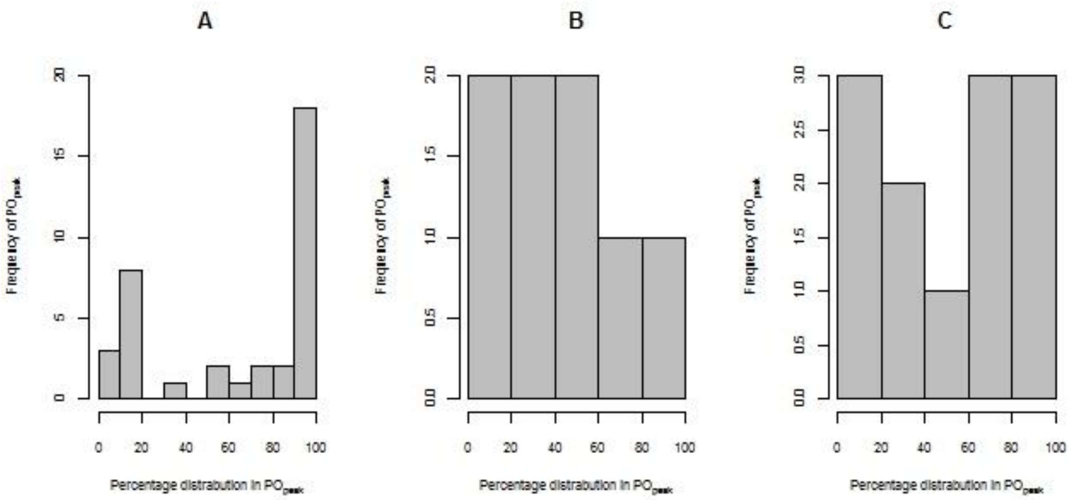

Figure 3.1: The percentage frequency distribution of PO_{peak} occurrences during flat (A, *n* = 37), semi-mountainous (B, *n* = 8) and mountainous (C, *n* =12) stages.

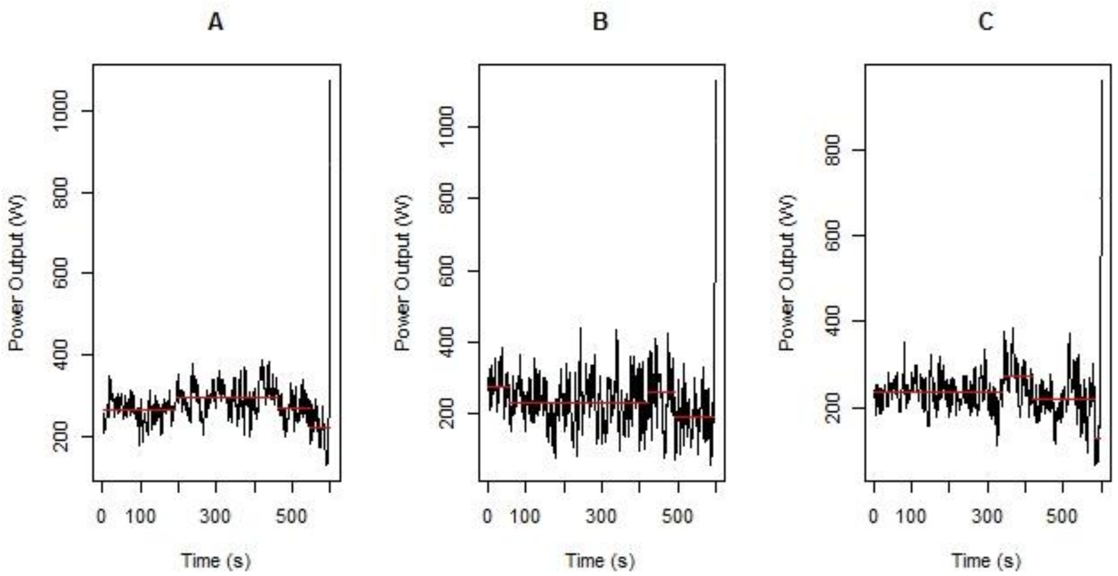

Figure 3.2: An example of the stochastic distribution of absolute power output before PO_{peak} using changepoint analysis across flat (A), semi-mountainous (B) and mountainous (C) stages in a single professional male road cyclist.

Table 3.1: Power output and length of time for each changepoint segment in topography categories (mean ± SD) [95% CI].

Topography Categories	Power Output and Time	Segment One	Segment Two	Segment Three	Segment Four	PO_{peak}
Flat	*Power Output (W)*	272 ± 125	316 ± 236	369 ± 173*	235 ± 179***	823 ± 213
		[230, 315]	[236, 396]	[310, 427]	[175, 296]	[751, 895]
***n* = 37**	*Time (s)*	228 ± 153*	109 ± 125	111± 113	121 ± 131**	29 ± 70
		[176, 280]	[66, 151]	[73, 150]	[77, 166]	[5, 53]
Semi-Mountainous	*Power Output (W)*	319 ± 185	186 ± 83*	512 ± 205*	157 ± 123***	886 ± 51
		[164, 474]	[116, 256]	[340, 683]	[54, 260]	[843, 928]
***n* = 8**	*Time (s)*	212 ± 152	199 ± 171	63 ± 83	120 ± 93*	4 ± 2
		[85, 339]	[55, 342]	[6, 133]	[39, 201]	[2, 5]
Mountainous	*Power Output (W)*	220 ± 117	184 ± 153	404 ± 229	171 ± 119***	656 ± 125
		[145, 295]	[86, 281]	[259, 552]	[95, 247]	[577, 736]
***n* =12**	*Time (s)*	240 ± 173	191 ± 141	77 ± 109	76 ± 55*	14 ± 19
		[130, 350]	[101, 281]	[8, 147]	[41, 111]	[1, 28]

* P <0.05, ** P <0.01, *** P <0.001; significant difference from left-to-right.

3.5 Discussion

The primary purpose of this study was to describe the frequency distribution of PO_{peak} values from different stage topography categories (flat, semi-mountainous and mountainous) in professional road cyclists. In line with our hypothesis, a higher frequency of PO_{peak} values (54%) occurred during flat stages in the final 80 to 100% of race time compared with the previous 0 to 80% of race time (46%) (Figure 3.1). Furthermore, the frequency of PO_{peak} values from semi-mountainous and mountainous stages were comparatively more evenly distributed compared with flat stages. The secondary purpose of this study was to analyse the power output 600 s prior to PO_{peak} values using a novel changepoint method across different stage topography categories (flat, semi-mountainous and mountainous). In flat stages, while power output increased from segment one to two, a decrease was observed from segment three to four (Table 3.1). Furthermore, contrary to our hypothesis, power output did not linearly increase in semi-mountainous and mountainous stages prior to PO_{peak}. Power output was significantly greater in flat and semi-mountainous topography categories from segment three to segment four.

The frequency distribution of PO_{peak} values from different stage topography categories are shown in figure 3.1. To the author's knowledge, this is the first time in which the frequency distribution of PO_{peak} values have been described in professional road cyclists. Interestingly, figure 3.1 demonstrates that PO_{peak} values are more likely to occur in the first or final 20% of a flat road race. Semi-mountainous stages demonstrated that 75% of PO_{peak} values occur between 0 to 60% of race time whereas 50% of PO_{peak} values during mountainous stages occur between 60 to 100% of race time. Typically, high-intensity efforts are performed early in an attempt to separate from a group of cyclists or late when few cyclists remain in the group (74). As well as multiple high-intensity efforts, Abbiss et al. (74) demonstrated a short period (~ 30 - 60 s) of low power output (100 - 300 W) prior to a breakaway or attack. A similar finding was observed in our study with power output in both flat and semi-mountainous stages significantly decreasing from segment three compared with segment four. However, the time spent in a low power output in segment four was twice as long (~ 120 s) in flat and semi-mountainous stages compared with mountainous stages (76 s) similar to Abbiss et al. (74) (~ 30 - 60 s) description. It is plausible that the reduced length of time in low power output is due to the characteristics of mountainous stages. Mountainous stages require longer periods of constant power output due to uphill cycling compared with flat stages (12, 13). It is plausible that PO_{peak} efforts are occurring during periods of sustained effort. Therefore, lower periods of time at a low-intensity power output is unsurprising.

In the present study, power output was analysed using a novel method called ‘changepoint’, demonstrated in figure 3.2. The analysis was able to highlight where the greatest changes in power output occur more easily than a visual estimation from a coach or exercise physiologist. It was hypothesised that power output would increase prior to PO_{peak} during flat stages. Indeed, power output increased between segment one and two (272 vs. 316 W). However, a significant decrease in power output was observed between segment three and four (369 vs. 235 W). This decrease could be due to participants’ knowledge of their requirements to soon conduct a maximal effort. Interesting, a decrease between segment three and four was also observed in semi-mountainous and mountainous stages (521 vs. 157 and 404 vs. 171 W respectively). This finding is contrary to the study by Menaspà et al. (159) who observed an increase in power output prior to PO_{peak}. However, data within this present study was from the entire stage whereas in Menaspà et al. (159) was directly before final stage sprints. This is important as cyclists have knowledge that the final stage sprint is about to happen whereas, in the present study, cyclists may or may not have knowledge of the impending PO_{peak} effort. However, as 54% of PO_{peak} values were conducted in the final 80 to 100% of flat race time, most PO_{peak} efforts occurred during final sprints.

A benefit of the analysis used in Study One was that the four largest changes in power output within the 600 s prior to the PO_{peak} were statistically determined (Figure 3.2), rather than an aribitary selection process as conducted in previous research (159). This analysis provided differing increments in time thus is important in the development of ecologically valid road cycling simulation protocols.

In calculating the mean power output and time of each changepoint segment for each rider, the stochastic nature of power was reduced. In doing so, key parts of the analysis may have been lost. Therefore, the use of changepoint as a tool for the analysis of time series power output data may be only applicable in individualised power output files as shown in figure 3.2. Unfortunately within this study it was not possible to quantify the role of each rider. It is plausible that the role of each rider may influence the interpretation of the data analysed. In this study, three riders were analysed in each event however, their roles may have change from one event to another.

3.6 Practical Application

The ability to describe and understand power output prior to PO_{peak} values will assist coaches in matching training programs. Moreover, changepoint analysis may assist in better understanding power output data from professional road cycling and ensure the development of more accurate laboratory based trials.

3.7 Conclusion

In conclusion, the frequency distribution of PO_{peak} values changed in races of varying topography with a higher frequency occurring at the end of flat stages. Changepoint may be able to provide a more detailed understanding of the variability within power output during cycling.

4 CHAPTER FOUR

EFFECTS OF TOPOGRAPHY, ROAD GRADIENT AND RIDER SPECIALITY ON MAXIMAL MEAN POWER OUTPUT DURING PROFESSIONAL CYCLING

4.1 Abstract

Introduction: A common method used in the performance analysis of a cyclists is the determination of maximal mean power (MMP). ***Purpose:*** The purpose of this study was to examine if MMP outputs differ across various topographies and rider specialities within grand tour cycling events. ***Methods:*** Power output was collected from 13 professional male cyclists during a total of 229 mass start stages of three grand tour cycling events between 2011 and 2015. The MMP obtained for 5, 15, 30, 60, 300, 600, 1200, 1800, 2400 and 3600 s were compared between stages of varying topography (flat (n = 104); semi-mountainous (n = 57); mountainous (n = 68)) and between riders of differing specialities (domestiques (n = 5); climber (n = 4); sprinter (n = 2); general classification (n = 2)). The proportion of race time spent in eleven power bands, ranging from less than 0.75 to greater than 7.5 $W{\cdot}kg^{-1}$, was compared between categories of topography, rider speciality and road gradient (<0%, 0 to 5% and >5%) . ***Results:*** MMP for durations longer than 1200 s were greater in semi-mountainous and mountainous stages, when compared with flat stages (1200 s: 5.1 ± 0.2, 5.2 ± 0.3, 4.5 ± 0.3 $W{\cdot}kg^{-1}$ respectively; P <0.05). Sprinters and climbers spent greater percentage of race time at a power output greater than 7.5 $W{\cdot}kg^{-1}$, when compared with general classification riders and domestiques (11.3, 11.4, 7.1 and 5.3%, respectively; P <0.05). A greater proportion of race time was spent at a power output above 3.7 $W{\cdot}kg^{-1}$ when cycling at a road gradient greater than 5% (P <0.05), compared with road gradients 0 to 5% and less than 0%. ***Conclusion:*** Topography, gradient and rider speciality influence the MMP values observed during grand tour races. Caution should be taken when comparing and interpreting MMP values between cyclists of differing speciality or when obtained from races of varying gradients and topographies. These results have implications for calculations that may rely on MMP values, such as the estimation of critical power.

Keywords: *Physical capacities, Power meter, Environment.*

4.2 Introduction

Cycling is a unique and demanding sport. Intensity during cycling exercise is highly variable and influenced by a range of factors including race format (i.e. time-trials, short circuit of criterium events or longer road races) (8), topography categories (i.e. flat, semi-mountainous or mountainous) (10, 15, 36), rider specialities (i.e. climbers, sprinters or domesiques) (1, 26, 41-43) and race dynamics (i.e. team and individual tactics) (74). The demands of professional road cycling have been described using heart rate (11, 12, 56), the rate of perceived exertion (83) and power output (9, 10, 14, 18, 26) . Typically, these studies distribute raw data into intensity zones. For example, Ebert et al. (9, 10) compared 0 to 100, 100 to 300, 300 to 500 and greater than 500 W power output intensity zones between differing topography categories. These zones provide a general indication of external load but, they do not provide an indication of maximal exercise capacities.

Several studies have examined the MMP output produced by cyclists over given durations (i.e. typically 1 - 3600 s) during competition. Such data are thought to be important because they may provide valuable information regarding a cyclist's capabilities. Indeed, Quod et al. (27) showed that a cyclist's MMP outputs, measured over a range of durations (5, 15, 30, 60, 240 and 600 s) in the laboratory, accurately reflect maximal aerobic capacity and MMP observed from the analysis of competition data. Consequently, several studies have used MMP obtained from professional road cyclist's field data as a method of analysing performance (25-27, 44).

Given that the MMP is the maximal power output an athlete achieves over a given duration, it is believed to be important in talent identification (25, 44) and monitoring performance (26, 27). It is, therefore, important to understand any external factors that may influence MMP other than the cyclist's physical capacity. Several studies have demonstrated MMP changes on differing topographies (15, 36), however, one of these was a case study of a single cyclist (36). To date, only one study has been published comparing MMP between different rider specialities (26). The authors observed sprinters recording the greatest 1 and 5 s MMP outputs while climbers recorded the greatest 5 to 60 s MMP outputs. But, this study was conducted throughout the course of a season. It is common that MMP are analysed for weekly and monthly comparisons, therefore, an understanding of changes during short periods is required. Collectively, these studies indicate that MMP outputs could be influenced not only by the cyclists' capacity but also the topography of the event and rider specialities. However, limited research has been conducted comparing MMP outputs within grand tour cycling events.

It is plausible that changes in road gradient between topography categories causes an adjustment in the MMP outputs. Indeed, Sassi et al. (154) demonstrated that both speed and freely chosen cadence decrease in a linear fashion from -4% to 12% road gradient. To date, the distribution and the amount of time spent during professional road races in differing power output zones in different road gradients is unknown.

The primary aim of this study was to examine if MMP outputs during grand tour cycling events differ across various topographies and rider specialities. It was hypothesised that MMP would increase on mountainous stages compared with flat stages. It was also hypothesised that sprinters would have the greatest peak MMP outputs (1 and 5 s) compared with all other rider specialties. Furthermore, that longer MMP outputs (~ 15 - 60 s) would be lower in domestiques compared to all other rider specialities due to the constant power output required to protect other rider specialities. The secondary aim of this study was to determine if the percentage of race time spent in different power output bands differs between categories of topography, road gradient and rider speciality during a grand tour. It was hypothesised that the percentage of race time in greater power outputs will be greater in mountainous stages, sprinters, climbers and on steeper (> 5%) road gradients.

4.3 Methods

4.3.1 Participants

Thirteen male professional cyclists (mean ± SD: age 25 ± 3 y, mass 69 ± 7.5 kg, height 178 ± 0.5 cm) participated in this study. Participants were members of two different professional cycling teams. All participants gave their written informed consent prior to data analysis. The study was approved by the Edith Cowan University Human Research Ethics Committee in accordance with the declaration of Helsinki.

4.3.2 Race and rider characteristics

Power output in this study was collected from 13 grand tour events between 2011 and 2015. Each of the grand tours covered approximately 3000 km over 21 stages with 2 rest days. A total of 273 stages were recorded with 44 missing or removed stages leaving 229 stages analysed in this study. Missing stages were unavailable either because recordings were not conducted or were removed from analysis due to loss of data. Stages were categorised based upon topography, and included 104 recordings of flat stages, 57 recordings of semi-mountainous stages and 68 recordings of mountainous stages. Time trial stages were eliminated from analysis. The topography of each stage was classified according to the distance cycled uphill and the TEG during each stage (102, 210). TEG was calculated from elevation data measured with a barometric altimeter. Flat stages were classified where total uphill riding distance was less than 13 km and a TEG of less than 800 m. Semi-mountainous stages were classified where a total uphill riding distance was between 13 and 35 km and a TEG of between 800 and 2000 km. Mountainous stages were classified where total uphill cycling distance was greater than 35 km and TEG was greater than 2000 m. Riders were categorised based upon specialty, and included 36 recordings of sprinters, 85 recordings of domestiques, 69 recordings of climbers and 39 recordings of general classification riders.

Categorisation was determined by the role of the rider in their team during the grand tour (personal communication by the team's coaches). Sprinters were racing to win stages in bunch sprints, general classification riders were racing for top ten place in the final general classification, climbers were racing to win stages during semi-mountainous or mountainous stages, and domestiques were racing to help other teammates. The distribution of stage type per rider is presented in table 4.1.

Table 4.1: Distribution of the different stages per cyclist.

Rider Speciality	Number of Recordings	Flat	Semi – Mountainous	Mountainous
Climber	17	9	3	5
Climber	19	10	3	6
Climber	19	10	3	6
Climber	14	7	3	4
Domestique	16	10	2	4
Domestique	19	10	3	6
Domestique	16	4	7	5
Domestique	17	7	6	4
Domestique	17	5	7	5
Sprinter	17	8	3	6
Sprinter	19	10	3	6
General Classification	19	7	7	5
General Classification	20	7	7	6
Sum	229	104	57	68

4.3.3 Power measurements

Power output was recorded throughout each stage using mobile SRM power meters (SRM Trainingsystems, Schoberer Rad Messtechink, Julich, Germany). The validity and reliability of the SRM devices have been previously reported (45, 51). It has also been demonstrated to provide accurate and reliable measurement of TEG (210), however, weather conditions causing a reduction in barometric pressure may reduce accuracy (211). The zero offset of the power meters were completed by the riders in accordance with the manufacturer's instructions prior to the start of each stage. Power values were recorded at a frequency of 1Hz. Power meter recordings were downloaded using SRM Training software (v6.42.18, Schoberer Rad Messtechnik, Germany). Power values were analysed using Golden Cheetah (v.3.1.0) and Microsoft Excel 2012 (Microsoft, USA). Power output data are presented relative to individual body mass ($W \cdot kg^{-1}$).

4.3.4 MMP calculation

The MMP output achieved by cyclists over time periods of 1, 5, 15, 30, 60, 300, 600, 1200, 1800, 2400 and 3600 s were determined for each rider on each stage. These time periods were based on prior research (25, 26, 44). All stage files were separated into topography categories and rider specialities. MMP was then calculated for each topography category and rider speciality.

4.3.5 Power output distribution

Power output was seperated into eleven discrete power bands for the determination of percentage race time previously used in the literature (22). These power bands included power output of less than 0.75, 0.76 to 1.50, 1.51 to 2.25, 2.26 to 3.00, 3.01 to 3.75, 3.76 to 4.55, 4.56 to 5.25, 5.26 to 6.00, 6.01 to 6.75, 6.76 to 7.50 and greater than 7.5 $W \cdot kg^{-1}$. The race time spent in differing power output bands was determined for topography categories, road gradients and rider specialities. Specifically, road gradients were banded as less than 0%, 0 to 5% and greater than 5%.

4.3.6 Statistical analysis

The MMP for topography categories and rider specialities were compared using a two-way repeated measures ANOVA. The percentage of race time in power output bands were compared within topography categories, rider specialities and road gradients using a one-way repeated measures ANOVA. Where significant effect was observed, Tukey-Kramer-HSD post-hoc test was applied. Statistical analyses were performed using SPSS, version 23 (Chicago, Illinois, USA). Results are presented as means ± standard deviation (mean ± SD). For all variables, statistical significance was accepted at P <0.05.

4.4 Results

4.4.1 MMP

The MMP curves for topography categories and rider specialities are shown in figures 4.1 and 4.2, respectively. The MMP in both semi-mountainous and mountainous stages for periods longer than 1200 s were greater (P <0.05) compared with flat stages (Figure 4.1). No differences (P >0.05) were observed in any other comparisons (Figure 4.1).

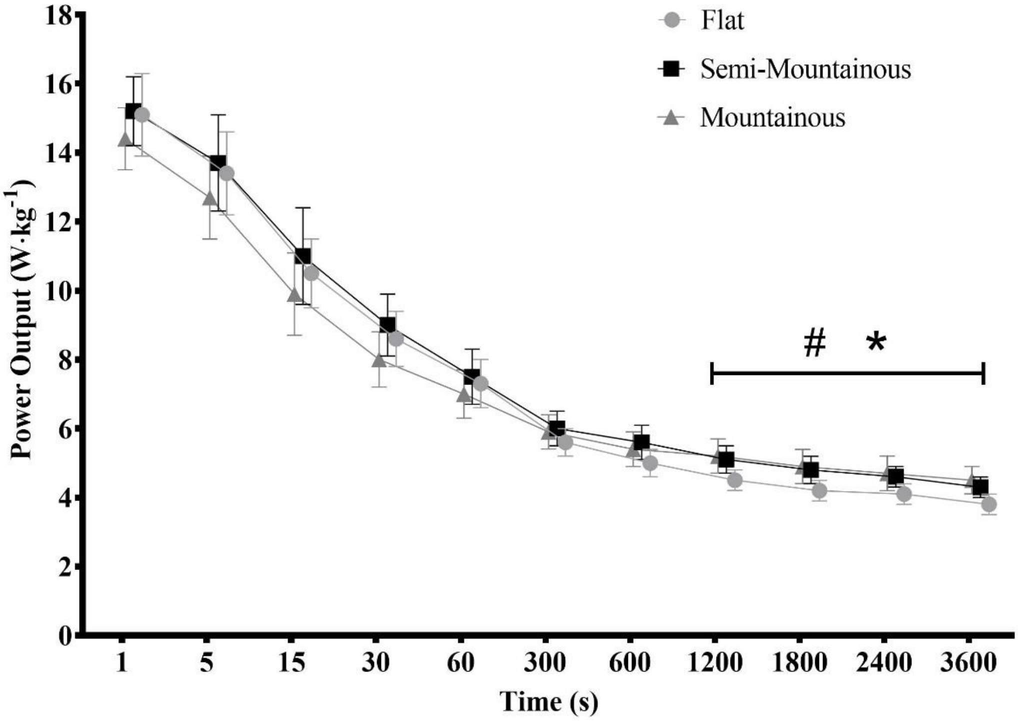

Figure 4.1: Relative MMP output of professional road cyclists during flat (n = 104), semi-mountainous (n = 57) mountainous (n = 68) stages of grand tours (mean ± SD) (P <0.05: * flat vs. semi-mountainous; # flat vs. mountainous).

The MMP observed over 1 and 5 s was greater (P <0.05) in general classification riders, when compared with both domestiques and sprinters (Figure 4.2). MMP averaged over 15 s was greater (P <0.05) in climbers compared with domestiques (Figure 4.2). The MMP observed over 30, 60, 300 and 600 s was greater (P <0.05) in general classification riders, compared with domestiques (Figure 4.2). The MMP over 600, 1200 and 1800 s was greater (P <0.05) in general classification riders, compared with sprinters (Figure 4.2). No differences (P >0.05) were observed between rider specialities across 30, 2400 and 3600 s (Figure 4.2).

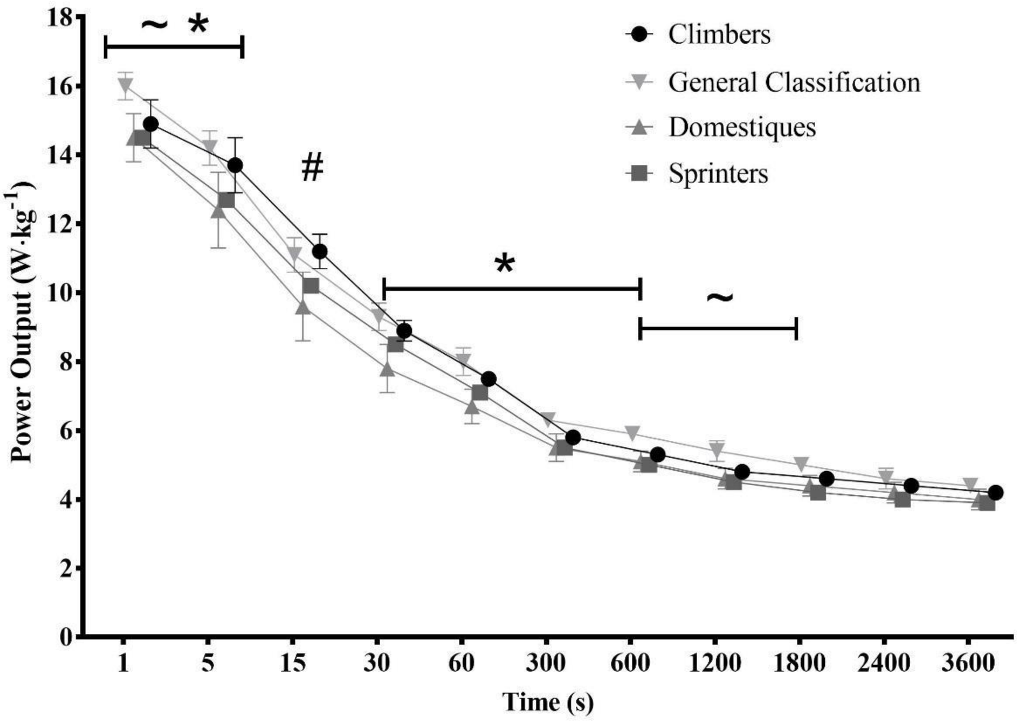

Figure 4.2: Relative MMP for durations 1-3600 s distributed for rider specialities domestiques (n = 85), sprinters (n = 36), climbers (n = 69) and general classification riders (n = 39) (mean ± SD) (P <0.05: ~ general classification vs. sprinters, * general classification vs. domestiques, # climbers vs. domestiques).

4.4.2 Power output distribution

The percentage of stage duration spent within discrete power bands across stages of varying topography (A) riders of differing speciality (B) and across varying road gradients (C) are presented in figure 4.3. The time spent in lower power bands (< 0.75, 0.76 - 1.50 and 1.51 - 2.25 $W \cdot kg^{-1}$) was greater (*P* <0.05) in flat stages, compared with semi-mountainous and mountainous stages (Figure 4.3A). The percentage of race time spent between 2.26 and 3.00 $W \cdot kg^{-1}$ was greater (*P* <0.05) in flat stages, compared with mountainous stages (Figure 4.3A). The time spent between 3.01 and 6.00 $W \cdot kg^{-1}$ was greater (*P* <0.05) in both semi-mountainous and mountainous stages compared with flat stages (Figure 4.3A). A greater (*P* <0.05) amount of time was spent between 6.76 to 7.50 $W \cdot kg^{-1}$ during semi-mountainous stages, compared with mountainous stages (Figure 4.3A). A greater (*P* <0.05) amount of time was spent above 7.5 $W \cdot kg^{-1}$ power band in the mountainous stages compared with semi-mountainous stages (Figure 4.3A). No differences (*P* >0.05) were observed in any other topography comparison.

Climbers spent greater (*P* <0.05) percentage of race time at power outputs lower than 0.75 $W \cdot kg^{-1}$ when compared with domestiques (Figure 4.3B). Domestiques spent greater (*P* <0.05) percentage of race time at power outputs lower than 1.51 to 2.25 $W \cdot kg^{-1}$ when compared with climbers (Figure 4.3B). Domestiques spent greater (*P* <0.05) percentage of race time at power outputs 2.26 to 4.55 $W \cdot kg^{-1}$ when compared with all other rider specialities (Figure 4.3B). General classification riders spent greater (*P* <0.05) percentage of race time at power outputs 5.26 to 6.00 $W \cdot kg^{-1}$ and 6.01 to 7.50 $W \cdot kg^{-1}$ when compared with sprinters and domestiques (Figure 4.3B). Climbers spent greater (*P* <0.05) percentage of race time at power outputs 6.01 to 7.50 $W \cdot kg^{-1}$ when compared with domestiques (Figure 4.3B). General classification riders spent greater (*P* <0.05) percentage of race time at power outputs 6.76 to 7.50 $W \cdot kg^{-1}$ when compared with domestiques (Figure 4.3B). Domestiques spent greater (P <0.05) percentage of race time in power outputs greater than 7.50 W·kg^{-1} when compared with general classification riders (Figure 4.3B). Sprinters spent greater (P <0.05) percentage of race time in power outputs greater than 7.50 W·kg^{-1} when compared with domestiques (Figure 4.3B). No differences (P >0.05) were observed in any other rider comparison.

The percentage of race time at gradients less than 0% was greater (P <0.05) at power outputs less than 0.75 W·kg^{-1} when compared with 0 to 5% and greater than 5% road gradient (Figure 4.3C). The percentage of race time at gradients between 0 to 5% was greater (P <0.05) at power outputs less than 0.75 W·kg^{-1} when compared with greater than 5% road gradient (Figure 4.3C). The percentage of race time at gradients between 0 to 5% was greater (P <0.05) at power outputs 0.76 to 3.00 W·kg^{-1} when compared with road gradient less than 0% and greater than 5% (Figure 4.3C). The percentage of race time at gradients greater than 5% was greater (P <0.05) at power outputs 3.76 to greater than 7.5 W·kg^{-1} when compared with road gradients less than 0% and 0 to 5% (Figure 4.3C). No differences (P >0.05) were observed the percentage of race time in any other gradient comparison.

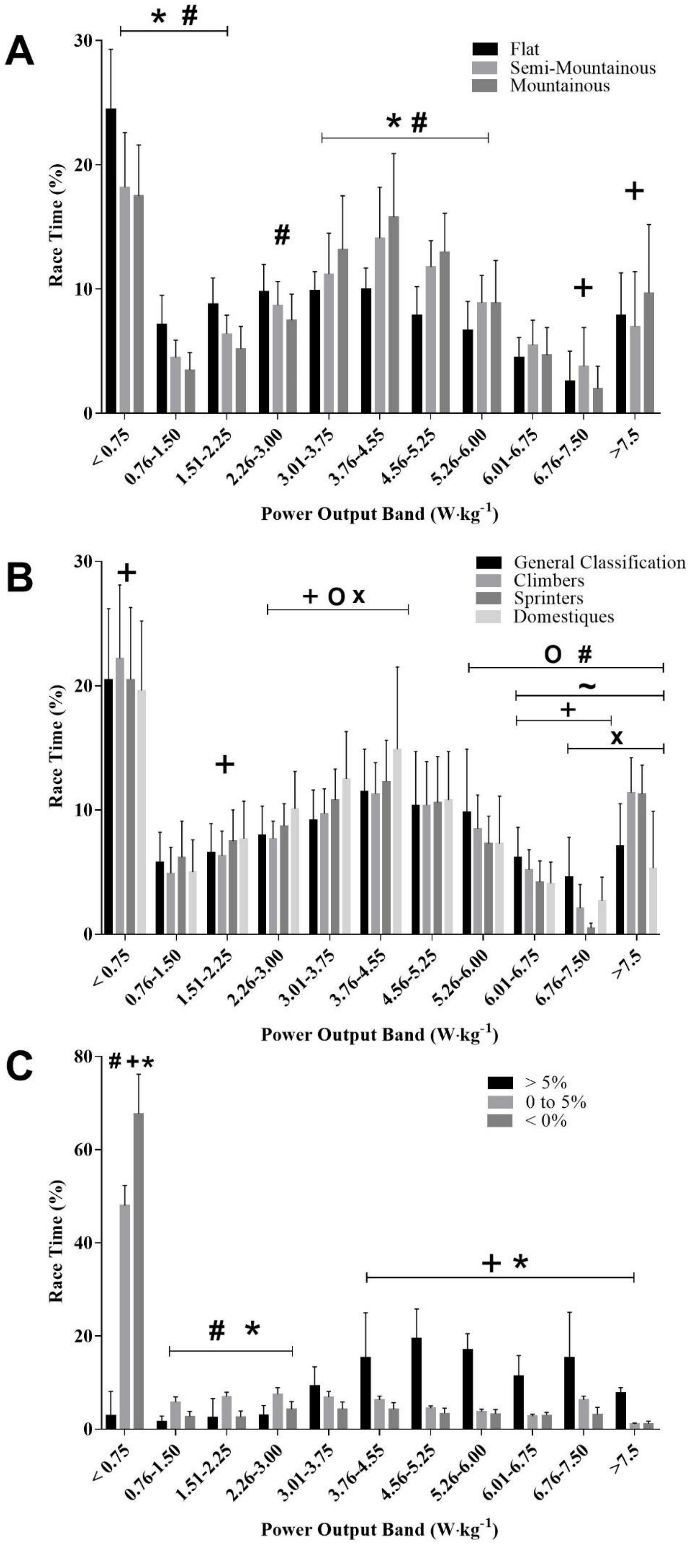
A
Flat
Semi-Mountainous
Mountainous
Race Time (%)
Power Output Band (W·kg-1)
< 0.75
0.76-1.50
1.51-2.25
2.26-3.00
3.01-3.75
3.76-4.55
4.56-5.25
5.26-6.00
6.01-6.75
6.76-7.50
>7.5
B
General Classification
Climbers
Sprinters
Domestiques
C
> 5%
0 to 5%
< 0%

Figure 4.3: Influence of relative topography categories (A) rider specialties (B) and road gradients (C) on power output distribution during grand tours. Data are divided into 0.75 $W \cdot kg^{-1}$ power bands and expressed as a percentage of total race time (Mean ± SD) (P <0.05; A: * flat vs. semi-mountainous; # flat vs. mountainous, +semi-mountainous vs. mountainous B: + domestiques vs. climbers, ~ general classification vs. climbers, ○ general classification vs. domestiques, X sprinters vs. domestiques, # sprinters vs. general classification. C: # <0% – 0 to 5%, + <0% – >5%, * 0% to 5% – >5%).

4.5 Discussion

The primary aim of this study was to examine if MMP during grand tour cycling events differs across various topographies and rider specialities. In accordance with our hypothesis, MMP output longer than 1200 s significantly increased on mountainous stages compared with flat stages (Figure 4.1). Furthermore, MMP changed depending on rider specialities (Figure 4.2). The secondary aim of this study was to determine if the percentage of race time spent in power output bands differs between categories of topography, road gradient and rider speciality during a grand tour.

In this study it was found that MMP output over longer durations (> 1200 s) were greater in semi-mountainous and mountainous stages compared with flat stages (Figure 4.1). Furthermore, while not significant, MMP for mountainous stages was lower than both flat and semi-mountainous stages between 1 and 60 s (Figure 4.1). This is probably due to the constant power output required while riding uphill in mountainous stages (Figure 4.3), rather than short explosive efforts required in flat stages. Results are similar to that of Vogt et al. (15) who observed greater power output in mountainous stages for long durations (> 1800 s) and lower output for short durations (< 15 s) in professional cyclists during a grand tour. There are several possible reasons for this increase including longer time spent at greater power output intensities, tactics and road gradient. The distribution of race time in power output bands on different topography categories and increasing road gradients differed (Figure 4.3A). The distribution showed semi-mountainous stages had significantly greater race time spent at power output intensities of 3.01 to 3.75 up to 5.27 to 6.00 $W \cdot kg^{-1}$ compared with flat stages (Figure 4.3A). It could be related to tactics as mountainous stages are important tactical sections of a race which are very reliant on aerobic capacity (13). Riders deliberately increase power output during uphill cycling to alter the race, however, little research has been conducted on the tactics of professional road cycling.

Several studies have demonstrated power output to be greater during uphill cycling exercise compared to flat (37, 38). Therefore, this could be the case for increased MMP outputs during longer durations. However, this is under the assumption that all MMP values recorded were indeed maximal values. These MMP outputs were the maximal values from each individual cyclist and it is plausible that these values do not reflect maximal physiological limits. However, it could also be argued that field power meter data provide a more accurate representation of actual MMP, when compared to laboratory testing. This is because it is highly likely that performance during racing is maximal. Whether maximal values were achieved over the range of durations and environmental conditions examined in this study is not clear and warrants further investigation. Regardless, these results have implications for the monitoring of performance and load of cyclists. It has been suggested that MMP from races may provide an indication of changes in fitness (25, 27, 44). This study indicates that caution should be taken because MMP values may need to be determined over both flat and mountainous stages.

MMP for rider specialities revealed significant differences, predominantly around the general classification riders (Figure 4.2). General classification riders showed the highest 1 and 5 s time point power output values of 16 ± 0.4 and 14.2 ± 0.5 $W \cdot kg^{-1}$, respectively, and constantly maintained high power output values during middle time points of 60 to 600 s (Figure 4.2). This is highly surprising as it was hypothesised that sprinters would demonstrate the greatest 1 and 5 s MMP. It is plausible that the MMP of sprinters over 60 and 300 s within this study were not maximal. Indeed, race dynamics and tactics are likely to heavily influence the MMP values observed during actual competition. Previous research has demonstrated sprinters peak power around 17.4 $W \cdot kg^{-1}$, that is ~ 3 $W \cdot kg^{-1}$ greater than the sprints in this study (165). It is plausible that the two sprinters analysed in this study were not the same quality as previous studies or that there were few sprints in which they were involved in. Also, the general classification riders may have been required to produce maximal efforts themselves during a stage attack. Although not significant, general classification riders appeared to be greater than domestiques between 800 and 1800 s (Figure 4.2). This is surprising as teams protect general classification riders with domestiques for the mountain stages which are considered the hardest sections of any grand tour, and where the race is often won or lost. At this time, attacks (riding away from a group of cyclists) are established in final climbs to build stage time gaps, ensure victory or to build time gaps in the overall tour standings. For example, while on the flat, it has been reported that numerous short (5 - 15 s), high intensity (~ 9.5 - 14 W·kg^{-1}) surges are typically observed before an attack (74). During this section of the race greater power output is observed in relation to the challenging topography and increased demand is placed on domestiques to protect general classification riders for as long as possible.

Similar to topography category race intensities, rider speciality showed large amounts of time in power outputs of less than 0.75 and greater than 7.5 W·kg^{-1} (Figure 4.3B). Domestiques and general classification riders showed significantly lower race time than sprinter and domestiques in power output greater than 7.5 W·kg^{-1}. The domestiques spent the majority of their race time in medium power bands (2.26 - 3.00, 3.01 - 3.75 and 3.76 - 4.55 W·kg^{-1}, Figure 4.3B). It is plausible that this is due to the majority of demestiques energy being used protecting general classification riders. The general classification riders were also looking to save energy. Consequently, little time was spent at very high power outputs. However, figure 4.2 demonstrated general classification riders maintained higher power outputs compared with all other riders between 600 and 1800 s. Sprinters produce high bursts of power output (165), but this study also demonstrates that climbers also put out greater power outputs with 11.4% of race time spent at greater than 7.5 W·kg^{-1}. If climbers are to win a stage, they need to maintain a relatively high power output (>

$7.5 W \cdot kg^{-1}$) when they are attacking in the mountains, however, high power outputs in sprinters occur in the build up to a sprint (159, 165).

In this study race intensities on differing road gradients were measured (Figure 4.3C). As road gradient increased, cyclists produced greater power outputs (Figure 4.3C) to overcome the resistive forces of gravity, and maintain their speed. Studies on pacing during different road gradients have demonstrated that maintaining power output results in the most optimal uphill performance (117). This could be tactical in response to an increase in race intensity from other riders. However, it could also be due to cyclists needing to produce greater power output on uphill sections of road. Regardless, this study shows that cyclists are required to produce considerable high-intensity efforts ($> 7.5 W \cdot kg^{-1}$) at high cycling road gradients (Figure 4.3C). Given that the position/angle of the bike changes cycling biomechanics (109, 112, 153) and muscle recruitment strategies (214-217) these results may be important in the preparation of athletes for competition. Indeed, rather than performing interval training on flat ergometers, athletes may wish to consider spending a significant proportion of high-intensity training on higher gradients.

4.6 Conclusion

In conclusion, the results of this study indicate that MMP output changes in differing topography categories and rider specialities during grand tour cycling events. Furthermore, race time spent in higher power output bands on steeper road gradients could have caused the MMP output for topography to change. Consequently, caution should be taken when analysing the MMP in relation to topography categories and rider specialities, and when considering the data, which is highly stochastic as an indicator of fitness.

5 CHAPTER FIVE

ESTIMATION OF CRITICAL POWER IN PROFESSIONAL ROAD CYCLISTS

5.1 Abstract

Introduction: It has been demonstrated that MMP is affected by topography, possibly due to differing road gradients. ***Purpose:*** To examine if estimated CP changes when calculated from stages of differing topography. Also to compare estimated CP from a FLAT and UPHILL field-based test. ***Methods:*** In Part 1, grand tour power output data (n = 219 stages) from thirteen professional male road cyclists were used to calculate CP. CP was estimated from the MMP achieved by cyclists over 12, 7 and 3 min of each stage. Stages were separated into one of three topography categories (flat (n = 97), semi-mountainous (n = 60) and mountainous (n = 62)). In Part 2, a single professional road cyclist performed three maximal efforts of 12, 7 and 3 min on both FLAT (mean gradient 0.4%) and UPHILL (mean gradient 6.2%) roads. For both parts, linear regression analysis from MMP outputs and maximal efforts of 12, 7 and 3 min were used to estimate CP. ***Results:*** In Part 1, no differences (P >0.05) were observed in estimated CP between all topography category comparisons. A large effects size (d = 0.8) was observed for differences in CP between flat stages and both semi-mountainous and mountainous stages. In Part 2, estimated CP was 11.6% lower in FLAT field-based test, compared with the UPHILL field-based test (5.0 vs. 5.6 $W \cdot kg^{-1}$). ***Conclusion:*** This study demonstrates a large difference between estimated CP values from alternative topography categories and from two different gradient specific field-based tests. It is recommended that CP is estimated using topography categories. Caution should also be taken when estimating CP from MMP values. A field-based test may be an appropriate alternative for measuring CP.

Key Words: *Power Output, Gradient, Uphill, Modelling.*

5.2 Introduction

The critical power concept represents the curvilinear relationship between work rate and exercise duration described in a hyperbolic equation (178):

$$\boldsymbol{t} = \frac{\boldsymbol{W'}}{(\boldsymbol{P} - \boldsymbol{CP})}$$

CP measurement has been demonstrated to represent an important predictor and fatigue threshold of endurance exercise performance (28, 29, 197). Exercise maintained below CP is theoretically based upon aerobic metabolism with an unlimited capacity but limited in rate (28). Exercise above CP is often regarded as anaerobic, defined as anaerobic work capacity (AWC), and represents a finite work capacity available to the athlete. While referred to as AWC, recent research indicates that work capacity above CP is not influenced entirely by anaerobic metabolism (29, 218).

For cycling exercise, CP can be measured in the laboratory. However, the majority of cyclists have limited access to regular laboratory facilities. Recent studies (33, 34, 186) have begun to look at the feasibility of an accurate and reliable single field-based test to measure CP during cycling. For instance, Karsten et al. (34) have reported that three separate field-based cycling tests may provide similar reliability in the estimation of CP. In particular, CP and AWC were determined using a field-based test which comprised of a 12 min, followed by a 7 min and a final 3 min maximal efforts with 30 min low-intensity recovery time in between. The protocol resulted in a high level of agreement (-2 ± 12 W) and low CP prediction errors (< 5%). The field-based test also provides a more ecologically valid testing environment compared with laboratory testing. While power recorded from training and racing may provide an accurate estimation of CP (15, 36), previous research and findings from Chapter Four indicate that MMP may differ on different topographies. The calculation of CP may be different due to the changes in road gradient.

During uphill cycling, task demands change with the increased gradient resulting in a lower speed and freely chosen cadences (155), changes to muscle recruitment strategies (214-217) and cycling biomechanics (109, 112, 153). As a result, it seems plausible that a change in road gradient will influence estimation of CP. For instance Nimmerichter et al. (38) have found that trained cyclists produce greater power outputs during a 20 min uphill (8.5% gradient) time trial compared with a flat time trial. Greater power outputs were accompanied with higher heart rates and blood lactate concentrations indicating a greater physiological strain during uphill time trials. Recently, Bouillod et al. (219) observed power output to be 11% greater during uphill compared with level ground cycling exercise in the field.

Thus, the primary aim of this study was to examine if estimated CP changes when calculated from stages of differing topography (flat vs. semi-mountainous vs. mountainous) within grand tour cycling events. It was hypothesised that CP estimated from grand tour race data will be greater in semi-mountainous and mountainous stages, when compared with flat stages. The secondary aim of this study was to compare estimated CP determined from a field-based test performed by a professional cyclist on level ground (FLAT) and while cycling uphill (UPHILL). It was hypothesised that estimated CP determined from an UPHILL test would be greater than a FLAT test.

5.3 Methods

This methodology section is broken down into two parts: Part 1 and Part 2.

5.4 Part 1

5.4.1 Participants

Data from thirteen professional male road cyclists (age 29 ± 4 y, height 171 ± 0.9 cm, mass 67 ± 8.2 kg) from two professional cycling teams were analysed. The cyclists were classified as level 5 based on the study by De Pauw et al. (209). The rider classification by team coaches included two sprinters, five domestiques, four climbers and two general classification riders. All participants gave their written informed consent. The study was approved by the Edith Cowan University Human Ethics Research Committee.

5.4.2 Experimental design

In total, 219 power meter files were analysed from grand tour events between 2013 and 2016. Stage files were classified into three topography categories, including flat (n = 97), semi-mountainous (n = 60) and mountainous (n = 62). Categories were determined based upon the TEG and the average percentage gradient of each cyclist. Stage topography was classified using previously published research (102) as well as updating the classification criteria using the TEG provided by the power meter during each stage. TEG is calculated from elevation data measured with a barometric altimeter. The SRM power meter has been demonstrated to provide accurate and reliable measurement of TEG (210), however, weather conditions causing a reduction in barometric pressure may reduce accuracy (211). Specifically, the average percentage gradient of each cyclist is the calculated mean slope for a whole stage duration. Flat stages were defined as stages of less than 2000 m TEG and less than 1.2% average gradient. Semi-mountainous stages were defined as a TEG between

2000 and 3000 m and between a 1.2 and 1.8% average gradient. Mountainous stages were defined as of greater than 3000 m TEG and greater than 1.8% average gradient. These classification criteria resulted in 97 flat, 60 semi-mountainous and 62 mountainous stages being analysed.

5.4.3 SRM measurements

All cyclists had SRM power meter systems (SRM Trainingsystems, Schoberer Rad Messtechink, Julich, Germany) mounted on their bikes during each grand tour stage and each CP field-based test. The power meter collected power output, altitude and road slope (gradient) at 1 Hz. The validity and reliability of the SRM devices (45, 51) and their measurement of TEG (210, 211) have been previously reported. All cyclists manually performed the zero-offset before each race and the SRM PowerControl was also set to automatically perform the zero-offset. All power output data were collected as absolute power (W) and were reported relative to body mass ($W \cdot kg^{-1}$).

5.4.4 Estimated CP and AWC

MMP output over durations of 12, 7 and 3 min durations were calculated for all stages. MMP outputs were plotted into a linear regression curve to calculate an estimated CP and AWC for each stage. Specifically, CP was estimated as P = AWC*(1/t) + CP where AWC is the anaerobic work capacity and 1/t is power-1/time. Once CP and AWC had been calculated for all stages, the mean 12, 7 and 3 min MMP, CP and AWC were calculated for topography categories.

5.5 Part 2

5.5.1 Participant

The cyclist was a single professional male road cyclist (age 25 y, height 164 cm, mass 55.0 kg) specialising as the general classification rider for a grand tour race. The rider was classified as level 5 based on the study by De Pauw et al. (209) and had previously finished in the top 3 of a grand tour 26 days prior to the start of data collection in this study. The rider also finished top 3 in the grand tour which took place in August/September 2016, 10 days after the final data collection ride. The rider gave his written informed consent and the study was approved by the Edith Cowan University Human Ethics Research Committee.

5.5.2 Experimental design

The participant performed two field-based cycling tests, one on a flat (FLAT) section of road and another on an uphill (UPHILL) section of road. Thirty-two days prior to these trials the participant performed a familiarisation trial of an identical protocol (described below). The familiarisation trial was performed on a level ground section of road. The FLAT field-based test was conducted on a tarmac road surface at an environmental temperature of 18.8 ± 2.6 °C (14 - 25 °C). The mean gradient of FLAT was 0.4 ± 0.1%. The UPHILL field-based test was conducted on a similar tarmac road with an environmental temperature of 14.7 ± 1.7 °C (12 - 20 °C). The mean gradient of UPHILL was 6.2 ± 0.1%. Both tests were conducted at a moderate altitude with the FLAT trial at an altitude between 2550 and 2590 m and the UPHILL trial beginning at 2537 m and finishing at 2832 m (+295 m). FLAT and UPHILL tests were separated by 10 days and the final test was conducted ten days prior to the start of a grand tour. Training sessions were conducted the day before both FLAT (93 km, 3h 10 min) and UPHILL tests (124 km, 3h 20 min). The rider consumed the same diet (including caffeine) prior to testing.

5.5.3 *CP field-based test protocol*

A self-selected warm up of 1 hour low-intensity cycling was conducted on a flat tarmac road prior to both FLAT and UPHILL field-based tests (3.0 and 3.1 $W \cdot kg^{-1}$ respectively). After a warm up, the participant was instructed to cycle as fast as possible for exercise durations in the order of 12, 7 and 3 min. The cyclist was instructed to continue low-intensity exercise for 30 min between each effort which has been found to be adequate for determining a valid CP (33, 34, 220). During each effort the cyclist was free to alter their own gear ratio and cadence. The cyclist was also able to see their time, power output and cadence throughout the tests. The same road bike was used for all tests. Once obtained, MMP outputs were then used to estimate CP and AWC using a previously validated and reliable field-based test (34). The average MMP outputs for 12, 7 and 3 min efforts were plotted, and using linear regression, CP and AWC values were determined as described in Part 1.

5.5.4 *SRM, estimated CP and AWC*

See as per Part 1.

5.5.5 *Statistics*

In Part 1, a two-way ANOVA was used to compare MMP outputs 12, 7 and 3 min over different topography categories. In Part 2, a one-way ANOVA was used to compare the estimated CP and AWC across topography categories. Where significant interaction and effects were observed, Tukey's post hoc test was applied. The 95% confidence intervals [95% CI] were also calculate for MMP, CP and AWC. To allow for a better interpretation of the results, effects sizes (Cohen's *d*) were also calculated and presented. Values of 0.2, 0.5, 0.8 and above 1.3 were considered small, medium, large and very large effects, respectively (221). Statistical analysis was conducted using IBM SPSS Version 21. Statistical significance was accepted at $P < 0.05$.

5.6 Results

Part 1

The MMP, CP and AWC for topography categories are shown in table 5.1. No differences (P >0.05) were observed between 12, 7 and 3 min MMP outputs across the three topography categories (Table 5.1). A medium effects size for 12 min MMP was observed in flat stages compared with semi-mountainous stages (d = 0.5). A small effects size for 12 min MMP was observed in flat stages compared with mountainous stages (d = 0.4) (Table 5.1). A small effects size for 7 min MMP was observed in flat stages compared with semi-mountainous stages (d = 0.3) (Table 5.1). No effect (d = <0.2) was observed in any other MMP comparisons (Table 5.1). No differences (P >0.05) were observed in either estimated CP or AWC across the three topography categories (Table 5.1). A large effects size for CP was observed in semi-mountainous (d = 0.8) and mountainous stages (d = 0.8), compared with flat stages (Table 5.1). A small effects size for AWC was observed in flat stages compared with semi-mountainous stages (d = 0.4) (Table 5.1). No effect (d = <0.2) was observed in any other CP or AWC comparisons (Table 5.1).

Part 2

The MMP, CP and AWC from FLAT and UPHILL tests are shown in table 5.2. MMP for 12, 7 and 3 min was 0.5 $W \cdot kg^{-1}$ (8.6%), 0.3 $W \cdot kg^{-1}$ (5.1%) and 0.1 $W \cdot kg^{-1}$ (1.4%) greater in UPHILL test compared with FLAT test (Table 5.2). Estimated CP for the UPHILL test was 0.6 $W \cdot kg^{-1}$ (11.3%) greater, compared with the FLAT test (Table 5.2). Estimated AWC for the FLAT test was 0.1 kJ (66.6%) greater, compared with the UPHILL test (Table 5.2).

Table 5.1: MMP outputs over 12, 7 and 3 min and estimated CP and AWC from flat, semi-mountainous and mountainous grand tour stages (Part 1; n = 13).

MMP		**Flat (*n* = 97)**	**Semi-Mountainous (*n* = 60)**	**Mountainous (*n* = 62)**
12 min ($W \cdot kg^{-1}$)	Mean ± SD	5.6 ± 0.9	6.0 ± 0.8	5.9 ± 0.7
	95% CI	5.0, 6.1	5.5, 6.4	5.5, 6.3
	Effects Size	0.5[a]	0.1[b]	0.4[c]
7 min ($W \cdot kg^{-1}$)	Mean ± SD	6.4 ± 0.9	6.4 ± 0.8	6.3 ± 1.0
	95% CI	5.5, 6.6	5.9, 6.8	5.8, 6.8
	Effects Size	0.4[a]	0.1[b]	0.2[c]
3 min ($W \cdot kg^{-1}$)	Mean ± SD	6.9 ± 0.8	7.0 ± 1.0	6.8 ± 0.9
	95% CI	6.3, 7.3	6.4, 7.6	6.2, 7.3
	Effects Size	0.1[a]	0.2[b]	0.1[c]
Estimated CP ($W \cdot kg^{-1}$)	Mean ± SD	5.2 ± 0.9	6.0 ± 1.1	5.8 ± 0.6
	95% CI	4.6, 5.8	5.3, 6.6	5.3, 6.1
	Effects Size	0.8[a]	0.2[b]	0.8[c]
AWC (kJ)	Mean ± SD	0.2 ± 0.1	0.4 ± 0.8	0.3 ± 0.7
	95% CI	0.1, 0.3	0.0, 0.9	0.1, 0.7
	Effects Size	0.4[a]	0.1[b]	0.2[c]

Effects size denotes: [a] flat, compared with semi-mountainous, [b] semi-mountainous-mountainous, [c] flat-mountainous.

Table 5.2: MMP outputs for 12, 7 and 3 min, estimated CP and AWC compared between FLAT and UPHILL field-based tests in a single professional male road cyclist (Part 2; Mean).

MMP	FLAT	UPHILL	Percentage Difference (%)
12 min ($W \cdot kg^{-1}$)	5.5	6.0	8.6%
7 min ($W \cdot kg^{-1}$)	5.7	6.0	5.1%
3 min ($W \cdot kg^{-1}$)	6.7	6.8	1.4%
Estimated CP ($W \cdot kg^{-1}$)	5.0	5.6	11.3%
AWC (kJ)	0.2	0.1	66.6%

5.7 Discussion

The primary aim (Part 1) of this study was to examine if estimated CP changes when calculated from stages of differing topography (flat vs. semi-mountainous vs. mountainous) obtained from race data during grand tours. Contrary to our hypothesis, no significant difference was observed in estimated CP between the three topography categories examined in this thesis. However, a large effect (d = 0.8) was observed for estimated CP between flat stages and both semi-mountainous and mountainous stages. The secondary aim (Part 2) of this study was to compare estimated CP determined from a field-based test performed by a professional cyclist on level ground (FLAT) and while cycling uphill (UPHILL). CP determined from the UPHILL field-based test was 0.6 $W \cdot kg^{-1}$ greater than the FLAT field-based test (Table 5.2).

Within this study it was hypothesised that CP would be greater in semi-mountainous and mountainous stages when compared with flat stages. This hypothesis was based on finding of Chapter Four, Nimmerichter et al. (38) and Bouillod et al. (219) who found that power output was greater during uphill road cycling conditions compared with flat road cycling conditions. Although not statistically significant (P >0.05), large effect sizes (d = 0.8) were observed for differences in CP between flat and both semi-mountainous and mountainous (i.e. 13.4% and 9.6%, respectively; Table 5.1). With such a large difference in CP between topography categories, the use of a single CP value is likely to result in substantial error for any modelling procedure. In Chapter Four, the MMP curve for flat stages was significantly lower in longer durations (> 1200 s) compared with semi-mountainous and mountainous stages. It was concluded that this was caused by cyclists producing greater power outputs for longer periods of time during uphill sections of the road. Other plausible explanations could be due to race dynamics or that cyclists can physically produce greater power output in uphill sections due to changes in muscle recruitment (214-217) and biomechanical position (109, 112, 153). However, the results from Part 2 indicate that a greater CP observed on uphill stages may not simply be because of race dynamics. Indeed, while topography influenced MMP and the estimation of CP based on the race data of thirteen professional road cyclists (Table 5.1) in Part 1, MMP calculated during maximal field-based tests in Part 2 were also greater during UPHILL compared with FLAT. Interestingly this greater CP during uphill cycling was despite these tests being done at altitude. Given the negative effects of altitude on MMP (62) it could be expected that CP would be lower during UPHILL since this trial ended some 300 m above FLAT and at moderate altitude (222). These results of Part 2 indicate that estimations of CP from competition data need to have sufficient flat and uphill data to be confident of a true CP.

In Part 1, substantial alterations were observed in estimated MMP outputs and CP between topography categories from 13 professional road cyclists (Table 5.1). Therefore, it may be beneficial to measure CP in the field on each specific topographic conditions (i.e. flat or uphill). In this study, Part 2 used a previously validated CP field-based test (34), comparing a flat-terrain (FLAT) with an uphill (UPHILL) test. The UPHILL test resulted in an 11.3% (0.6 $W \cdot kg^{-1}$) increase in estimated CP compared with the FLAT test (Table 5.2). While MMP outputs have been demonstrated to decrease at altitude during multi-stage racing (62), in this study, a constant 6% gradient appears to have increased MMP at 12, 7 and 3 min (Table 5.2) resulting in a greater estimated CP. While AWC was also calculated, previous research using the same protocol as this study has failed to provide robust validity of the measurement (220). Therefore, caution should be taken when considering the AWC results in this study until further validation. It is also plausible that cadence may have been an important factor in MMP values across gradients. Future research should examine cadence and its relationship with varying gradients.

Results from Part 2 were collected from a single professional road cyclist. While this cyclist was professional (level 5 (191) who finished twice in the top three in a grand tour), future research should examine the effects of road gradient on CP and AWC in larger population groups. It is also highly likely that this cyclist was very well trained in uphill cycling (given the importance to a general classification rider). Whether such differences are observed in cyclists from other specialities or differing skill level is not known.

5.8 Practical Applications

In this study, estimated CP can be calculated using MMP field-based data. While no significant differences were observed between topography categories, large effects sizes were measured. Therefore, it is recommended that multiple calculations of CP are conducting in different topographic conditions (i.e. flat or uphill) and used separately.

5.9 Conclusion

This study demonstrates that estimated CP values may differ between topography categories and from two different gradient specific field-based tests. Indeed, although not significant in Part 1, a large effects size was observed. A large effects size was also observed in Part 2 using a specific gradient field-based tests. It is recommended that estimated CP be calculated in separate topography conditions.

6 CHAPTER SIX

GRADIENT INFLUENCES CYCLING POWER OUTPUT DURING GRAND TOUR MOUNTAIN STAGES

6.1 Abstract

Introduction: Previously, differing topographies have been demonstrated to change MMP values. It has been suggested that such changes may be directly due to the effect of road gradient on MMP and thus CP. ***Purpose:*** To investigate the influence of road gradient on MMP from the mountainous stages of professional male road cyclists during grand tour events. ***Methods:*** Power output was collected from seven professional male road cyclists. A total of 50 mountain grand tour stage starts were analysed between 2011 and 2016. Power output and the road gradient were directly measured from SRM power meters. The rolling average for one and five min maximal mean powers (1 and 5 MMP) were calculated. The average 1MMP and 5MMP were calculated in road gradient bands (-5, -4, -3, -2, -1, 0, 1, 2, 3, 4 and 5 %). Power output in road gradient bands were compared from lowest to next highest (e.g. -3% to -2%). ***Results:*** Power output from road gradient -1% was lower (P <0.001) in both 1 and 5 MMP compared with 0% (2.4 to 3.3 and 2.2 to 3.1 $W \cdot kg^{-1}$ respectively). Power output from road gradient 1% was lower in both 1 (P <0.01) and 5 (P <0.05) MMP compared with 2% (3.6 to 4.2 and 3.4 to 4.1 $W \cdot kg^{-1}$). No difference (P >0.05) was observed between any other comparisons. ***Conclusion:*** Steeper road gradients resulted in both greater average 1 and 5 MMP in professional male road cyclist's during mountainous grand tour road stages. These results are not thought to be due to one factor but, multiple disciplinary factors including biomechanical position, cadence, gross efficiency and changes in muscular recruitment patterns.

Keywords: *Uphill, Performance Analysis, Power Meter.*

6.2 Introduction

Grand tours are the longest cycling events in the professional road cycling season. Professional male road cyclists will cover around 3000 km in 21 days (146) with only 2 days recovery in between. Within these events, semi-mountainous and mountainous stages are very important to the overall outcome of the race (particularly in the general classification and king of the mountains classification). During semi-mountainous and mountainous stages, several periods of time lasting between 30 to 60 min (223) are spent ascending and descending on different road gradients. Chapters Four and Five have observed that power output is greater during mountainous stages compared with flat stages using MMP and CP. It is plausible that greater power outputs were achieved on mountainous stages during the uphill sections of the stage. An MMP curve based on gradient is not possible due to lack of constant time spent above 300 s on steeper road gradients (Figure 8.2). However, quantifying power less than 300 s into road gradient bands is possible. It has been found that cycling uphill results in changes to biomechanical cycling position (112, 214, 224, 225), gross efficiency (37, 39), cadence and muscular recruitment patterns (217) compared with flat cycling.

When pedalling uphill in a seated position, greater force is produced at crank angle of 45° crank angle compared with cycling on the flat (156). Furthermore, when pedalling uphill cyclists are more likely to move into a standing position, drastically influencing the task demands of the activity. Indeed, research has shown that cycling in a standing position is more physiologically demanding (225), less economical at low intensities (153, 226) and produces greater maximal power outputs (112, 224). Muscle activation patterns have been demonstrated to be influenced by varying road gradients. Sarabon et al. (217) compared neuromuscular patterns in the lower extremity of twelve well-trained mountain bikers at alternating road gradients of 0, 10 and 20%. The authors found significant EMG neuromuscular pattern changes between 0 and 20% gradients concluding that these modifications in neuromuscular patterns would influence joint kinetics and efficiency during cycling exercise.

Differences in efficiency have been observed with standing, compared with seating studies (153, 226). Within the studies, a direct influence of gradient on cycling efficiency appears to be evident (37, 39). Specifically, on a treadmill Arkestejin et al. (37) found that gross efficiency was lower when cycling at 8% gradient, when compared with 4% and 0% road gradients. Likewise, Nimmerichter et al. (39) found that gross efficiency was greater (mean difference 1.3%) during a flat (1.1% gradient) compared with an uphill (5.1% gradient) cycling exercise protocol.

Overall, uphill cycling influences the bike position (153, 225, 226), task demands and, therefore, biomechanics (112, 214, 224, 225) and muscle recruitment strategies (214, 215, 217). These changes influence multiple factors including pedal force (156), maximal power outputs and fatigue development (112, 224). This is particularly the case during standing vs. seated cycling exercise (112, 153, 224, 225). It is, therefore, plausible that the MMP observed in mountainous stages, when compared with flat stages (Chapters Four and Five) is the result of a cyclist's ability to produce greater power output at increased road gradients. However, no study to date has examined power output on different gradients obtained in mountainous stages from professional road cyclist's field data. Therefore, the aim of this study was to investigate if road gradients cause a change in MMP from professional male road cyclists during mountainous stages from grand tour events. We hypothesise that the steeper the road gradient, the greater the MMP. Specifically, one and five min MMP outputs will be analysed due to the lack of time spent on constant steeper road gradients.

6.3 Methods

6.3.1 Participants

Data are from seven professional male road cyclists (age 30 ± 4 y, height 169 ± 8 cm, body mass 69 ± 9 kg) from two professional cycling teams were analysed. In total 50 mountainous stages were analysed in this study from grand tours between 2011 and 2016. The cyclists were classified as level 5 based on the study of De Pauw et al. (209). Furthermore, all had completed three or more grand tour cycling events. The riders gave their written informed consent. The study was approved by the Edith Cowan University Human Ethics Research Committee.

6.3.2 Experimental design

Mountainous stages were determined based upon the TEG (210, 211) and the average percentage gradient of each stage. TEG is calculated from a barometric altimeter in the power meter. The average TEG calculated from all race files analysed was 3837 ± 645 m. The cyclists each had an SRM power meter (SRM Trainingsystems, Schoberer Rad Messtechink, Julich, Germany) attached to their bikes during all stages of the grand tour. The SRM power meter has been demonstrated to provide accurate and reliable measurement of TEG (210), however, weather conditions causing a reduction in barometric pressure may reduce accuracy (211).

6.3.3 SRM measurements and data processing

Power output was recorded throughout each stage using mobile SRM power meters. The validity and reliability of the SRM devices have been previously reported (45, 51). The zero offset of the power meters were completed by the riders in accordance with the manufacturer’s instructions prior to the start of each stage. Power values were recorded at a frequency of 1Hz. Power meter recordings were downloaded using SRM Training software (v6.42.18, Schoberer Rad Messtechnik, Germany). Power values were analysed using Golden Cheetah (v.3.1.0) and Microsoft Excel 2012 (Microsoft, USA). Power output data is presented relative to individual body weight (W·kg^{-1}).

Road Gradient was analysed using Golden Cheetah (v.3.1.0**)** software termed as 'slope'. To allow for the analysis of road gradient, a spreadsheet (Excel, Microsoft, USA) calculated the one and five min rolling average in maximal mean powers (1MMP and 5MMP). The average 1MMP and 5MMP was calculated in road gradient bands -5, -4, -3, -2, -1, 0, 1, 2, 3, 4 and 5 %. To ensure graident was constant over each MMP duration, power output which was geater than 1SD was removed from analysis. Furthermore, the spreadsheet removed all data less than 5% and greater than 5% gradient due to lack of constant data above and below these gradients. In total 22342 ± 9897 data points were collected from the cyclists. Following data cleaning, a total of 13745 ± 8031 data points remained for 1MMP analysis and 4468 ± 1606 data points for 5MMP analysis. The average 1MMP and 5MMP was then calculated for each road gradient.

6.3.4 Statistics

For 1MMP and 5MMP a one-way ANOVAs were used to compare power output across road gradients. Where significant effect was observed, Bonferroni's multiple comparisons post-hoc test was applied. The 95% confidence intervals [95% CI] were also calculated for the power output. To allow for a better interpretation of the results, effects sizes (Cohen's *d*) were also calculated and presented. Values of 0.2, 0.5, 0.8 and above 1.3 were considered small, medium, large and very large effects, respectively (221). Statistical analysis was conducted using IBM SPSS Version 21. Statistical significance was accepted at P <0.05.

6.4 Results

The average 1MMP and 5MMP are demonstrated in table 6.1. Road gradients were compared from lowest to next highest road gradient power band (e.g. -3% to -2%).

For 1MMP, power output for road gradient -1% was lower (*P* <0.001) compared with 0% (2.4 ± 0.4 vs. 3.3 ± 0.6 $W \cdot kg^{-1}$ respectively) (Table 6.1). Power output for road gradient 1% was lower (*P* <0.01) compared with 2% (3.6 ± 0.5 vs. 4.2 ± 0.2 $W \cdot kg^{-1}$ respectively) (Table 6.1). No other differences (*P* >0.05) between comparisons were observed (Table 6.1).

Small effect sizes were observed between -4 to -3% and -3 to -2% (*d* = 0.3 and 0.2 respectively) (Table 6.1). A medium effect size was observed between 3 to 4% (*d* = 0.6) (Table 6.1). Large effect sizes were observed between -5 to -4%, -2 to -1% and 2 to 3% (*d* = 1.0, 1.0 and 1.0 respectively) (Table 6.1). Very large effect sizes were observed between -1 to 0% and 1 to 2% (*d* = 1.8 and 1.5 respectively) (Table 6.1). No effect (*d* = <0.2) was observed between 4% to 5% gradient (0) (Table 6.1).

For 5MMP, power output for road gradient -1% was lower (*P* <0.001) compared with 0% (2.2 ± 0.7 vs. 3.1 ± 0.5 $W \cdot kg^{-1}$ respectively) (Table 6.1). Power output for road gradient 1% was lower (*P* <0.05) compared with 2% (3.4 ± 0.4 vs. 4.1 ± 0.4 $W \cdot kg^{-1}$ respectively) (Table 6.1). No other differences (*P* >0.05) between comparisons were observed (Table 6.1).

Small effect sizes were observed between -3 to -2% and 3 to 4% (*d* = 0.3 and 0.2 respectively) (Table 6.1). Medium effect sizes were observed between -4 and -3%, -2 and -1%, 0 and 1% and 2 and 3% (*d* = 0.5, 0.5, 0.6 and 0.8 respectively) (Table 6.1). Very large effect sizes were observed between -1 and 0% and 1 and 2% (*d* = 1.5 and 1.7 respectively) (Table 6.1).

Table 6.1: 1 and 5 MMP for each road gradient between -5 and 5%.

Road Gradient		1MMP	5MMP
	Mean ± SD ($W{\cdot}kg^{-1}$)	1.2 ± 0.4	-
-5%	*95 % CI*	[1.0, 1.5]	-
	Effects Size	1.0	-
	Mean ± SD ($W{\cdot}kg^{-1}$)	1.7 ± 0.6	1.4 ± 0.5
-4%	*95 % CI*	[1.4, 2.0]	[1.0, 1.8]
	Effects Size	0.3	0.5
	Mean ± SD ($W{\cdot}kg^{-1}$)	1.9 ± 0.6	1.7 ± 0.7
-3%	*95 % CI*	[1.6, 2.2]	[1.2, 2.2]
	Effects Size	0.2	0.3
	Mean ± SD ($W{\cdot}kg^{-1}$)	2.0 ± 0.4	1.9 ± 0.5
-2%	*95 % CI*	[1.8, 2.2]	[1.6, 2.2]
	Effects Size	1.0	0.5
	Mean ± SD ($W{\cdot}kg^{-1}$)	2.4 ± 0.4***	2.2 ± 0.7***
-1%	*95 % CI*	[2.2, 2.6]	[1.8, 2.6]
	Effects Size	1.8	1.5
	Mean ± SD ($W{\cdot}kg^{-1}$)	3.3 ± 0.6	3.1 ± 0.5
0%	*95 % CI*	[3.1, 3.6]	[2.8, 3.4]
	Effects Size	0.5	0.6
	Mean ± SD ($W{\cdot}kg^{-1}$)	3.6 ± 0.5**	3.4 ± 0.4*
1%	*95 % CI*	[3.4, 3.8]	[3.2, 3.7]
	Effects Size	1.5	1.7
	Mean ± SD ($W{\cdot}kg^{-1}$)	4.2 ± 0.3	4.1 ± 0.4
2%	*95 % CI*	[4.0, 4.3]	[3.9, 4.4]
	Effects Size	1.0	0.8
	Mean ± SD ($W{\cdot}kg^{-1}$)	4.6 ± 0.5	4.5 ± 0.5
3%	*95 % CI*	[4.4, 4.8]	[4.2, 4.8]
	Effects Size	0.6	0.2
	Mean ± SD ($W{\cdot}kg^{-1}$)	4.9 ± 0.5	4.6 ± 0.3
4%	*95 % CI*	[4.6, 5.1]	[4.4, 4.8]
	Effects Size	0.0	-
	Mean ± SD ($W{\cdot}kg^{-1}$)	4.9 ± 0.5	-
5%	*95 % CI*	[4.6, 5.2]	-
	Effects Size	-	-

* P <0.05, ** P <0.01, *** P <0.001; significant difference for mean and effects sizes from respective value below (e.g. -5% to -4%, -4% to -3%).

6.5 Discussion

The aim of this study was to investigate if road gradients cause a change in MMP from professional male road cyclists during grand tour mountainous stages. We hypothesised that the steeper the road gradient, the greater the 1 and 5 MMP. Both 1 and 5MMP showed an increase in power output from lower to higher road gradients (Table 6.1). Significance was observed between -1 to 0% and 1 to 2% for both 1 and 5 MMP (Table 6.1). Furthermore, effects sizes supported an increase in power output with steeper road gradients for both 1MMP and 5MMP (Table 6.1). Multiple interconnecting factors have been proposed to explain the observed changes in average power output on alternative road gradients including biomechanical body position (seated vs. standing) (109, 112, 153), cadence (154, 156), gross efficiency (37, 39), muscular recruitment patterns (214, 216) and tactical decisions (74).

During uphill cycling, a change in the adopted body position on the bike shifts rider biomechanics. Previous research has demonstrated that when riding uphill, a more upright body position is adopted (109). To demonstrate this, Hansen et al. (112) compared power output in seated vs. standing during uphill cycling and showed that a greater power output could be sustained for longer (30-40 s) while standing than seated at 165% of W_{max}. It is, therefore, plausible that the greater power output values observed in this study had occurred when changing the angle of the bike influencing the biomechanics and body position.

With a change in the angle of the bike shifting biomechanics, greater hamstring activation occurs allowing for a more even torque distribution throughout the pedal stroke. Specifically, muscular recruitment is influenced by the change in body position and cadence during uphill cycling. Due to field-based race conditions, muscular recruitment could not be analysed in this study, however, based upon laboratory-based evidence (153, 214, 227), we can assume that muscular recruitment patterns changed during alternative road gradients. A change in muscle recruitment also influences the metabolic cost, resulting in uphill cycling being less efficient. For example, Arkestein et al. (37) observed a decrease in gross efficiency at both +4 and +8% compared with 0% gradient at the same work rates and cadence. Despite the high metabolic cost, this study found that both 1 and 5MMP are greater with increasing gradient. The effects of gradient on MMP appear maximal at gradients below -3% or above +3%. However, between-3%, 0 and +3% the effects seem more marked with a significant difference between -1 and 0% and 1 to 2% in both 1 and 5 MMP (Table 6.1). It is plausible that riders have reached either a physiological or biomechanical point at gradients greater or less than 3%. At which there is little can be done to mitigate the effects of the imposed gradient and performance is compromised.

During 5MMP, no data could be obtained at -5% and +5% road gradients. Data could not be obtained as there was no period of time long enough for 5 min at these road gradients. This demonstrates the similar issue with developing a gradient based power curve. Instead, rolling averages were used for 1 and 5 MMP. Several concerns have been with the use of rolling averages have been recently discussed within the literature (228). Menaspà et al. (228) states two main limitations in this process. The author states that averages overlook variations within a set period of time and obscure overall patterns. In this case, small spikes in 1MMP will be included into the 5MMP average. Also, the author states that rolling averages do not consider when a given stimulus happens within a set time frame. In this case, we do not know when the greatest 1 and 5 MMP occur throughout the stage, Future research should attempt to examine when the greatest MMP values are occurring similar to the PO_{peak} value analysis of Chapter Four. Furthermore, 17874 ± 8291 data points had to be removed when calculating 5MMP leaving 4468 ± 1606 remaining for analysis. Also, caution should be taken as a greater number of data points were examined during the shorter

1MMP compared with the longer 5MMP. The difference in data points between MMP values may have resulted in sample bias arising from more 1MMP values. Future research could look at power output on differing road gradients and controlled sample sizes in the laboratory. This will also provide the opportunity to investigate some of the mechanisms proposed from this field-based research study.

6.6 Practical Application

Practically, the method used in this study provides a simple way of quantifying average power output on alternative road gradients. The resulting output provides a power-gradient slope which can be used to assess the demands of mountainous stages.

6.7 Conclusion

In conclusion, increases in road gradient results in a greater average 1MMP and 5MMP in professional male road cyclists from grand tour mountainous road stages. These results are not thought to be due to one factor but, multiple disciplinary factors including biomechanical position, cadence gross efficiency and changes in muscular recruitment patterns.

7 CHAPTER SEVEN

THE WITHIN-SEASONAL DISTRIBUTION OF EXTERNAL TRAINING AND RACING WORKLOAD IN PROFESSIONAL MALE ROAD CYCLISTS

Metcalfe A.J, Menaspà P., Villerius V, Quod M, Peiffer J.J, Govus A.D, Abbiss C.R. The within seasonal periodisation of external training and racing workload in professional cyclists. *International Journal of Sports Physiology and Performance*: S2 142-146 (Impact factor: [2015: 3.042])

7.1 Abstract

Introduction. Professional road cyclists use power output to monitor changes in external workload during a season. ***Purpose:*** To describe the within-season external workloads of professional male road cyclists for optimal training prescription. ***Methods:*** Training and racing of four international competitive professional male cyclists (age 24 ± 2 y, body mass 77.6 ± 1.5 kg) were monitored for 12 months prior to the world team time trial championships. Three within-season phases leading up to the team time trial world championships on 20th Sept 2015 were defined as phase one (Oct - Jan), phase two (Feb - May) and phase three (June - Sept). Distance and time were compared between training and racing days and over each of the various phases. Time spent within absolute (< 100 W, 100 to 300 W, 400 to 500 W, > 500 W) and relative (0 to 1.9 $W \cdot kg^{-1}$, 2.0 to 4.9 $W \cdot kg^{-1}$, 5.0 to 7.9 $W \cdot kg^{-1}$, >8 $W \cdot kg^{-1}$) power zones were also compared for the whole season and between phases one to three. ***Results:*** Total distance (3859 ± 959 vs 10911 ± 620 km) and time (240.5 ± 37.5 vs 337.5 ± 26 h) was lower (P <0.01) in phase one than phase two, respectively. Total distance decreased (P <0.01) from phase two to phase three (10911 ± 620 vs 8411 ± 1399 km, respectively). Mean absolute (236 ± 12.1 vs 197 ± 3 W) and relative (3.1 ± 0 vs 2.5 ± 0 $W \cdot kg^{-1}$) power output was higher (P <0.05) during racing compared with training, respectively. ***Conclusion****:* Volume and intensity differed between training and racing over each of three distinct within-seasonal phases.

Keywords: *Time Trial, Power Output, SRM Powermeter, Training Load.*

7.2 Introduction

Understanding the external workload demands of professional road cyclists is necessary to optimise training, reduce the risk of injury and diagnose symptoms of overtraining (4). The use of power meters during professional cycling races and training allows for multiple external load measurements to be instantaneously collected during a ride. Athletes and sports scientists commonly analyse these measurements to assess performance and to aid in their decision making processes.

The external workload in professional male cyclists has been previously described during road racing (10, 15, 26, 36, 44) and training (19). While these studies add to a wealth of knowledge on external workload, the within-season distribution of workload during both training and racing is not well understood. Indeed, such research is limited to a detailed 50-week account of a world-class female triathlete in preperation for the Olympic-distance triathlon event (16).Therefore, the purpose of this study was to investigate the within-season distribution of external workload in four professional road cyclists throughout a cycling season and preparing for the world team time trial championships.

7.3 Methods

7.3.1 Participants

The training and racing of four professional male cyclists (mean ± SD: age 24 ± 2 y, body mass 77.6 ± 1.5 kg, height 184.0 ± 4.3 cm) from the same professional cycling team were monitored for 12 months (October 2014 - September 2015) prior to the world team time trial championships held on 20th September 2015, Richmond, USA. The cyclists were classified as level 5 based on the study of De Pauw et al. (209). Furthermore, all four cyclists had previously won a stage at the the *Giro d'Italia* and two were winners of national ITT and road racing events. Body mass measurements were taken in July/August 2015. All participants gave their written informed retrospective consent on the condition that individual data were reported as mean group data. The study was approved by the Edith Cowan University Human Ethics Research Committee.

7.3.2 Experimental design

In total 1124 training and racing files were retrospectively collated over the season with all participants competing in the team time trial at the championships. 56 files were removed due to error resulting in 1068 files retrospectively analysed. For the purpose of this study, the cycling season was defined as October 2014 to September 2015. Within-season periodised macro cycles were defined by coaches/sports scientists as general base preperation (phase one; Oct 14 Jan 15), racing (phase two; Feb 15 - May 15) and event preperation (phase three; June 15 - Sept 15). All riders had planned to peak at similar times during the season and took part in a *Giro d'Italia* grand tour cycling event in May 2015. The world team time trial championship was a flat (240 m elevation change) (210) 38.6 km event with the winning team completing the course in 42 m 07 s (55.2 $km \cdot h^{-1}$).

All training and racing data were collected using SRM (SRM Training Systems, Schoberer Rad Messtechnik, Jülich, Germany) power meters. All data were sampled at 1Hz. The SRM power meter device has been previously reported to have acceptable validity and reliability (45, 51). All power meter were statically calibrated at the beginning of the season (November/December) and re-calibrated if battery replacement occurred during the season. The SRM PowerControl was set to automatically perform the zero-offset for every session (training and racing). Following each training or racing session, race files were uploaded online with Training Peaks (Peaksware LLC, Lafayette, CO, USA) and later analysed using Microsoft Excel.

7.3.3 Data analysis

The total distance, time and mean absolute (W) and relative ($W \cdot kg^{-1}$) power output were measured over the whole season and compared between phases one to three. Each phase consisted of 17 weeks. The total volume and mean absolute and relative power output were also separated into racing and training days and compared over the whole season. Furthermore, total volume and power output during training and racing for each week and in separate phases (one to three) were compared. Time spent within discrete, previously defined (9, 10) exercise intensity power zones, in absolute (< 100 W, 100 to 300 W, 300 to 500 W and > 500 W) and relative values (0 to 1.9 $W \cdot kg^{-1}$, 2.0 to 4.9 $W \cdot kg^{-1}$, 5.0 to 7.9 $W \cdot kg^{-1}$and > 8.0 $W \cdot kg^{-1}$) were also evaluated between phases one to three.

7.3.4 Statistics

Linear mixed models were used to compare differences in mean total distance, time and mean power output overall, between training and racing days and the percentage of exercise intensity spent in each phase. Models were fitted using *nlme* package (Version 3.1-127) (229) and follow up tests were conducted using the *phia* package in the R statistical program (212). All models were compared to a null model (i.e. with no explanatory variables) using Akaike Information Criteria. Where necessary, models were fit with random intercept and slope to account for variable rates of change between each athlete and selected as the parsimonious model when minimising the AIC value. Two-tailed statistical significance was accepted at $P \leq 0.05$. Results are expressed as (Mean ± SD, [95% CI]).

7.4 Results

The total distance, time and mean power output for the whole season and during phases one to three are summarised in table 7.1. Total distance increased from phase one to phase two (40%; P <*0.05*). Furthermore, total distance decreased from phase two to phase three (-22%; P <0.01). Absolute mean power output decreased from phase two to phase three (-9%; P <0.01).

Table 7.1: The weekly total distance, time and mean power output absolute and relative for the whole season and during each periodised phase (Mean ± SD, [95% CI]).

	Whole Season (*n*=1068)	**Phase One (*n*=309)**	**Phase Two (*n*=399)**	**Phase Three (*n*=360)**
Weekly Total Distance (km)	508.6 ± 53.1 [424, 593.2]	396.4 ± 55.4* [308.2,484.7]	627 ± 35.8 [575.6,687.7]	486.1 ± 80.8* [357.5,614.9]
Weekly Total Time (h)	16.4 ± 1.5 [14,18.9]	13.9 ± 2.1* [10.4, 17.3]	19.4 ± 1.5 [17, 21.9]	16.8 ± 0.3 [13.6,20.2]
Absolute Power Output (W)	208 ± 5 [199, 218]	216 ± 9** [201, 231]	221 ± 8 [208,234]	201 ± 6* [191,211]
Relative Power Output ($W \cdot kg^{-1}$)	2.8 ± 0.3 [2.6, 2.9]	2.8 ± 0.3 [2.5, 3.2]	2.8 ± 0.3 [2.4, 3.3]	2.6 ± 0.3 [2.3, 3]

*Significantly different (P <0.05) from phase two, ** phase three.

The comparison of total training and racing distance, time and mean power output for the whole season and during phases one to three are summarised in table 7.2. Training time was higher (39%) than racing (P <0.05), training absolute mean power output was lower (19%) than racing (P <0.05). Racing distance increased by 192% from phase one to phase two (P <0.01). Racing time increased by 548% from phase one to phase two (P <0.01). The percentage of time in each exercise intensity zone across each phase is displayed in figure 7.1.

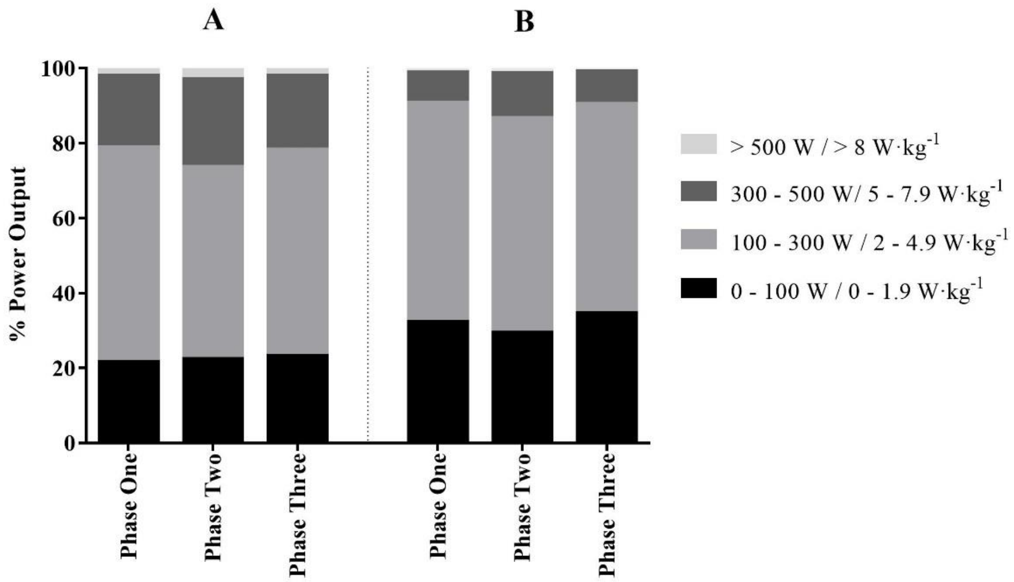

Figure 7.1: Mean time (expressed as a total percentage of A, absolute power output and B, relative power output) spent in exercise intensity zones during each phase. Standard deviations and statistical significance symbols have been omitted for the clarity of the figure.

Total time in the absolute 300 to 500 W and relative 5.0 to 7.9 $W{\cdot}kg^{-1}$ zone was higher in phase two compared to phase one (P <0.01). Total time in the absolute 100 to 300 W and relative 2.0 to 4.9 $W{\cdot}kg^{-1}$ zone was lower in phase two compared to phase one (P <0.01). Total time in the absolute 300 to 500 W and relative 5.0 to 7.9 $W{\cdot}kg^{-1}$ zone was lower in phase three compared to phase two (P <0.05). Total time in the 100 to 300 W and relative 2.0 to 4.9 $W{\cdot}kg^{-1}$ zone was higher in phase three compared to phase two (P <0.05). The total weekly differences in training and racing duration and distance are displayed in figure 7.2.

Table 7.2: The overall season volume (distance and time) and mean power output absolute and relative between training and racing. Also, phase volume and mean power output absolute and relative between training and racing (Mean ± SD, [95% CI]).

	Whole Season (*n*=1068)		**Phase One (*n*=309)**		**Phase Two (*n*=399)**		**Phase Three (*n*=360)**	
	Training (n=762)	Racing (=306)	Training (*n*=279)	Racing (*n*= 30)	Training (*n*=232)	Racing (*n*=167)	Training (*n*= 251)	Racing (*n*=109)
Total Distance (km)	14841 ± 2344 [11111,18571]	11457 ± 1023 [9829,13085]	5776 ± 1306 [3698,7855]	1214 ± 381 [608,1821]	4326 ± 1625 [1776,6947]	6549 ± 1580# [4034,9065]	4646 ± 393 [4021,5272]	5140 ± 1054 [3463,6818]
Total Time(h)	533 ± 58.1* [441.4,625.9]	322 ± 27.8 [277.8,366.2]	212.3 ± 34 [158.1,266.4]	28.2 ± 3.8 [22.1,34.3]	156 ± 46.6 [87.8,234.1]	183.8 ± 43.5# [114.5,253]	152.5 ± 19 [122,175]	140 ± 12 [25.6,254]
Absolute Power Output (W)	197 ± 8* [185, 210]	236 ± 12 [217, 255]	201 ± 6 [191,211]	233 ± 20 [200,266]	200 ± 9 [185,214]	242 ± 10 [225,259]	191 ± 9 [176,206]	216 ± 16 [191,242]
Relative Power Output ($W \cdot kg^{-1}$)	2.5 ± 0.1* [2, 2.9]	3.1 ± 0 [2.9, 3.2]	2.5 ± 0.1 [2.2, 2.8]	3.1 ± 0.1 [2.8, 3.4]	2.5 ± 0.1 [2.1, 2.9]	3.2 ± 0 [3, 3.3]	2.3 ± 0.1 [2, 2.6]	3 ± 0.1 [2.7, 3.2]

* Training was significantly different to racing in respective whole season and individual phases.

Significantly different (P <0.05) from phase one.

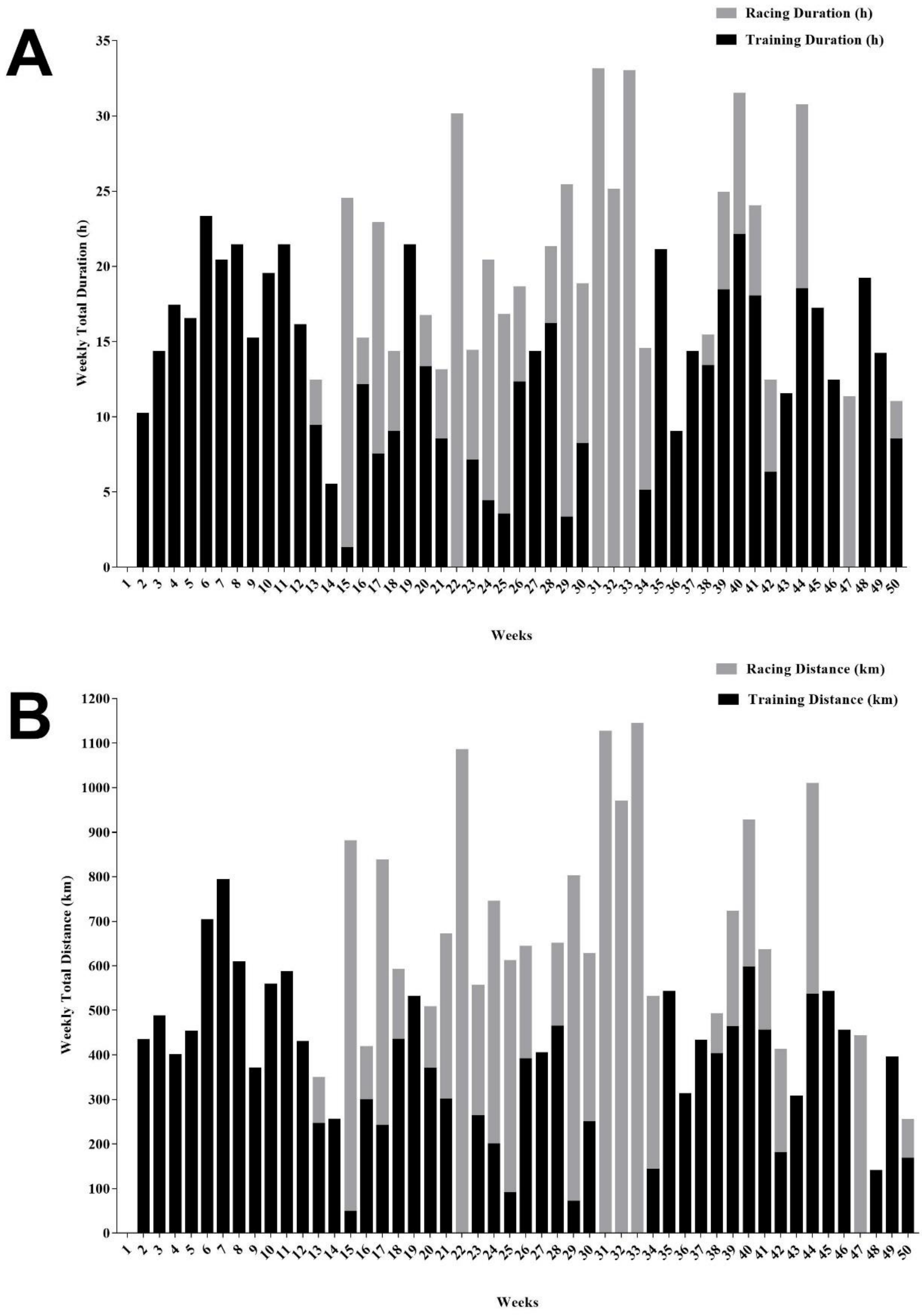

Figure 7.2: The mean weekly total duration (A) and distance (B) for training and racing over the whole season.

7.5 Discussion

The aim of this study was to investigate the within-season distribution of external workload in four professional male road cyclists racing throughout the cycling season and preparing for the world team time trial championships. The distribution in total volume (distance and time) covered was significantly lower during phase one compared to phases two and three (Table 7.1). Furthermore, the total racing volume (distance and time) significantly increased from phase one to phase two (Table 7.2).

The off-season period for these specific professional road cyclists was during phase one, resulting in the observed lower total cycling distance covered as well as lower total ride time (Table 7.1). While no differences were observed in relative mean power output between phases, a lower absolute mean power output during phase three compared to phases one and two (Table 7.1) was observed. It is plausible that during phase one, riders are completing longer aerobic based training (279 training vs. 30 race days) rides (Figure 7.2) compared to phase three (251 training vs. 109 race days), however, lower absolute and relative mean power output intensities were not significantly different between phases (Figure 7.1). It is unsurprising that phase two resulted in the highest absolute mean power output due to all riders inclusion in a grand tour event also resulting in the greatest amount of racing days during phase two (167 days). Post grand tour, riders conducted a lower intensity recovery period, possibly causing the lower absolute mean power output in the final phase. Furthermore, in preparation for the world team time trial championship, time was spent on time trial bikes which could cause an overall lower mean absolute power output.

Differences were observed in the time spent in absolute (100 to 300 W and 300 to 500 W) and relative (2.0 to 4.9 $W \cdot kg^{-1}$ and 5.0 to 7.9 $W \cdot kg^{-1}$) power output intensity zones (Figure

7.1). Time in the 300 to 500 W zone significantly increased from phase one (19%) to phase two (23.4%). An increase by 4% was also seen in the relative 5.0 to 7.9 W·kg^{-1} zone. This demonstrates that riders were spending more time at a lower intensity (100 to 300 W/2.0 to 4.9 W·kg^{-1}) during the off-season in phase one (Table 7.2). Much of this increase in cycling intensity is likely to be the result of greater racing in phase two. Indeed, by examining the week by week variation in training distance and duration (Figure 7.2), participants considerably reduce training load to compensate for increased competition. Whether or not such training optimally prepares athletes for competition is not clear. However, results of the present study highlight the training and competition demands of elite-level cyclists. As a result of the increased time during phase two in the absolute 300 to 500 W zone, a lower percentage time in the 100 to 300 W zone in phase two (51.2%) compared to phase one (57.3%) was observed. An observation also shared in the relative power output intensity zones. These results are similar to previously reported adjustments (19) in the training intensity of elite under 23 male road cyclists between winter and spring periods. Interestingly, phase three showed the reverse effect with time in the absolute 300 to 500 W zone decreasing (19.6%), resulting in an increase in time during the 100 to 300 W zone (55%), similar to phase one (57.3%). This observation is also supported by the relative power output with a 5.3% increase between phases two and three in the time spent at 0 to 1.9 W·kg^{-1}. Although a decline in overall training and racing volume would be expected in tapering preparations (230) for the world team time trial, a considerable reduction in the time spent at threshold (300 to 500 W/5.0 to 7.9 W·kg^{-1}) intensities was observed throughout phase three. The reduction in training volume at threshold throughout this phase, and not just in the taper for this event, could be due to riders spending a long period of time racing a grand tour event in phase two followed by short high intensity races in phase three (Figure 7.2).

A limitation of these observations in this study are that body mass was only measured at the end of the season (July/August). Variation in body mass during the season may have altered the measurement of relative power output and, therefore, influenced the interpretation of our data. Future research should regularly measure body mass throughout the season to obtain a more accurate determination of relative power output and provide individualised training zones.

7.6 Conclusion

In conclusion, this study describes the within-season distribution of external workload in four professional road cyclists. It was found that volume and intensity differed between training and racing over each of three distinct within-seasonal phases. This investigation provides a brief insight into within-seasonal training and racing differences in professional male road cyclists.

8 CHAPTER EIGHT

GENERAL DISCUSSION

8.1 Summary

This thesis examined multiple factors (e.g. topography, road gradient and rider) which influence power output and thus the quantification of external workload during single and multi-stage professional cycling events. This thesis also examined current methods used to measure and analyse cycling power output and investigated multiple methods to improve this process. The outcomes of this research provide new insights into how various environmental factors may influence the assessment of external workload within male professional cycling. An overview of the external work demands of such competition is also provided.

The primary purpose of Study One was to describe the frequency distribution of PO_{peak} values from different stage topography categories (flat, semi-mountainous and mountainous). It was hypothesised that a greater frequency of PO_{peak} values would occur during the final section (> 80% of the total race distance) of flat stage races as exercise intensity increases towards the finish. Indeed, 54% of PO_{peak} values did occur within the final 20% of flat stage races compared with 46% of PO_{peak} values between 0 to 80% of stage race time (Figure 3.1). It was hypothesised that during semi-mountainous and mountainous stages, the frequency of PO_{peak} values would be more evenly distributed across the stage races as fewer explosive high-intensity efforts are required/produced. Indeed, 75% of PO_{peak} values in semi-mountainous stages occurred between 0 to 60% of race time compared with 25% between 60 to 100% of race time (Figure 3.1). Whereas in mountainous stages 50% of PO_{peak} values occurred between 0 to 60% of race time with the other 50% of PO_{peak} values occurring between 60 to 100% of race time (Figure 3.1). These results demonstrated that differences occur in the distribution of PO_{peak} values during differing stages of varying topography. It is important to understand where PO_{peak} values are distributed as this will aid in understanding the stochastic nature of road cycling. It will also help in understanding where key points in a professional road race occur on differing topographies, possibly influencing tactical decisions.

The increase in frequency of maximal effort observed towards the end of flat stages in Study One was likely associated with the increased likelihood of a sprint finish in flat stages. Research has examined the power output requirements of professional road cyclists leading into a sprint finish and indicates that power output is extremely stochastic and gradually increases prior to the sprint (144). In a simulated trial Menaspà et al. (164) used three arbitrary time periods (10, 5 and 1 min) to mimic the power output demands in the 10 min prior to maximal sprint performance. A limitation of Menaspà et al. (164) is that the time periods were arbitrarily selected with little justification for the time periods chosen. Therefore, the secondary aim of Study One was to use a novel changepoint method to analyse the distribution of power output 600 s prior to PO_{peak} efforts in stages of differing stage topography (i.e. flat, semi-mountainous and mountainous). It was hypothesised that during flat stages, power output 600 s prior to PO_{peak} would progressively increase, as observed by Menaspà et al. (164). Furthermore, a more even distribution would be observed in power output prior to PO_{peak} in semi-mountainous and mountainous stages. In flat stages, while power output increased from segment one to two, a decrease was observed from segment three to four (Table 3.1). Power output did not linearly increase in semi-mountainous and mountainous stages prior to PO_{peak}. Power output was significantly greater in flat and semi-mountainous topography categories from segment three to segment four (Table 3.1). This is probably due to anticipation of a sprint or breakaway occurring.

Future research should look into sprints and breakaways to conform this observation in power output.

A benefit of the analysis used in Study One was that the four largest changes in power output within the 600 s prior to the PO_{peak} were statistically determined (Figure 3.2), rather than arbitrarily selected as in prior research (159). This analysis provided differing increments in time and is thus important in the development of ecologically valid road cycling simulation protocols. It is important to note that the analysis conducted in this study is probably best used on an individualised basis rather than grouped, as grouping the data together may cause the loss of individual responses, which is not useful for this type of analysis. Changepoint analysis could be used for any time series based data sets. For example, MMP is typically measured at a range of time points determined by the experimenter and not always consistent in the literature. For instance, Quod et al. (27) measured MMP at 5, 15, 30, 60, 240 and 600 s whereas Pinot and Grappe (26) measured MMP at 30, 60, 90, 120, 150, 180, 210 and 240 s. Changepoint analysis may provide an alternative method for determining of the ideal exercise durations to examine, while the number of time points to include may still be debatable. For example, figure 8.1 shows a power-duration time curve of a single professional road cyclist from a single stage. Rather than the investigator selecting where the MMP is calculated (i.e. 5, 15, 30 s etc.), changepoint determined the seven largest statistical adjustments across all power values within the stage. The outcome is an adjusted set of segments (highlighted in red) which would hypothetically increase and decrease in length depending on the factors alluded to within this thesis including topography categories, rider specialities and fitness.

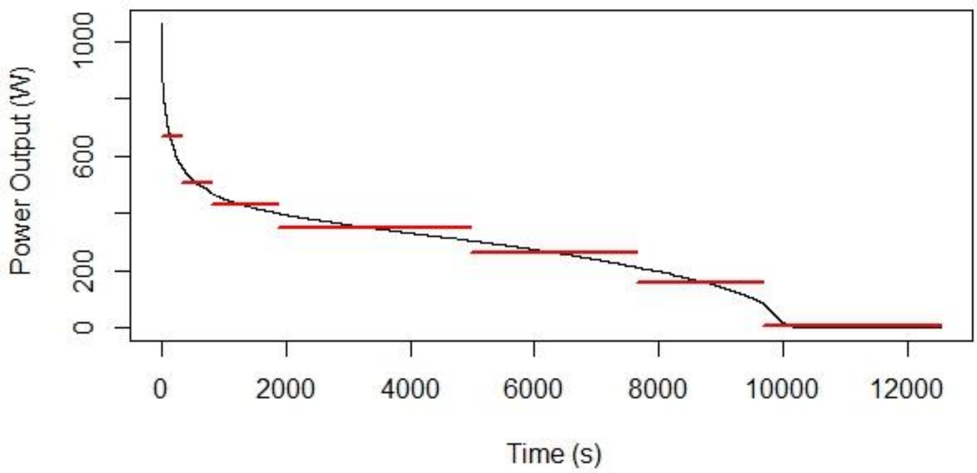

Figure 8.1: Example of a hypothetical changepoint analysis to develop a power-duration curve. Investigator based maximal power values have been removed and replaced by the seven biggest statistical changepoint segments using whole stage power output in a single professional male road cyclist.

The PO_{peak} values observed in Study One differed over stages of varying topography. This finding is not surprising since it has been demonstrated that MMP decreases during multi-stage racing at an altitude greater than 3000 m, compared with sea level (62). However, within this study, the decrease in MMP observed at 3000 m is likely due to the effects of altitude (i.e. partial pressure of oxygen) on aerobic function and athletic performance (62). While MMP has been investigated during multi-stage (27, 62), grand tour (15), within-season (25, 26, 30) and between seasons (44), only one study has directly examined MMP over differing topographies (15). Furthermore, only one study (26) has investigated any change in MMP between rider specialities. However, this study was conducted with 10 months of data, therefore, systematic studies on MMP during a variety of multi-stage races and grand tours are still required in order to better understand the specific demands of these events. It is also important to note that cycling stages of differing topography are not only influenced by altitude but also changes in road gradient, race dynamics and individual and team tactics, which may have varying effects on external workload demands. Consequently, the primary aim of Study Two was to examine if MMP differs across stages of various topographies and rider specialities. It was also hypothesised that MMP from shorter durations (~ 5 to 60 s) would be lower in domestiques compared to all other rider specialities due to the constant power output required to protect other rider specialities. It is also plausible that MMP observed over longer durations would be greater in domestiques compared with other rider specialities. A secondary aim of Study Two was to determine if the percentage of race time spent in different power output bands differs between categories of varying topography, gradient and rider speciality. It was hypothesised that the percentage of race time spent at high power outputs would be greater in mountainous compared with flat stages, steep (> 5%) compared with flat road gradients and in sprinters and climbers compared with domestiques and general classification riders.

Study Two found that MMP differs between topography categories and rider specialities. Specifically, power output averaged over durations longer than 1200 s were lower in flat stages, when compared with semi-mountainous and mountainous stages (Figure 4.1). These results are of importance since power output during mountainous stages may be compromised due to the increased likelihood of altitude negatively affecting aerobic performance. Instead, we observed greater MMP outputs over durations important in aerobic function (> 1200 s) during mountainous stages. It was concluded that a significantly greater portion of race time spent on steep gradients during semi-mountainous and mountainous stages allowed for prolonged periods of high power output. Indeed, the race time spent in power zones at different gradients from Study Two provide evidence for this conclusion. In Study Two, significantly more race time was spent in higher power output bands (3.76-4.55 to > $7.5 W \cdot kg^{-1}$) on road gradients of greater than 5% compared with road gradients of less than 5% (Figure 4.3C). Regardless of the causes of such differences, the findings indicate that it is important that researchers and coaches consider topography categories before analysing a cyclist's MMP. This is especially important when coaches and athletes may be using MMP from racing and training data to determine fitness characteristics of athletes (27). Utilising data from only one topography type may not provide a true indication of an athlete's performance capabilities. Furthermore, from these data it can be presumed that mathematical modelling which is reliant on such performance characteristics may be influenced by topography. Indeed, CP is commonly estimated using field-based MMP outputs (33, 34) and may be influenced by the topography over which field-based data are obtained.

Henceforth, the aim of Study Three was to examine if estimated CP differs when calculated from stages of differing topography (flat vs. semi-mountainous vs. mountainous). It was hypothesised that CP estimated from grand tour race data would be greater in semi-mountainous and mountainous stages, when compared with flat stages. No significant difference was observed in estimated CP from semi-mountainous and mountainous stages compared with flat stages (5.9 ± 1.1 and 5.7 ± 0.6 vs. 5.2 ± 0.9 $W \cdot kg^{-1}$ respectively; Figure 5.1). However, a large effect (*d* = 0.8) was observed in estimated CP from semi-mountainous and mountainous stages compared with flat stages. The influence of topography categories was unsurprising given that Study Two had already observed significant differences in grand tour MMP outputs from which the estimated CP values (12, 7 and 3 min) were derived. Consequently, both MMP outputs and estimated CP are influenced by topography categories. Indeed, the task demands, biomechanics, pedal force, economy and cycling pattern change when cycling on the flat and uphill and as such it is plausible that the change in MMP and consequently CP is because cyclists are able to produce greater power outputs at an incline. Therefore, the secondary aim of Study Three was to remove race dynamics and examine the performance capabilities of a professional road cyclist using FLAT and UPHILL field-based tests. Based on the findings in Study Two it was hypothesised that estimated CP determined from an UPHILL test would be greater than a FLAT test. CP during the UPHILL field-based test was 0.6 $W \cdot kg^{-1}$ greater than with the FLAT field-based test (Table 5.2). In this case, MMP, and consequently estimated CP, were greater when cycling uphill compared with on the flat. The tests were done at approximately 2500 m where an increased altitude should cause a decrease in power output (60, 231) resulting in lower aerobic function and, therefore, a lower CP. While previous studies have acknowledged the influence of road gradient in cycling speed and cadence (154), our understanding of road gradient on power output is limited. Furthermore, the results of Study Three have implications for research utilising CP for modelling (e.g. AWC) particularly when examining events where gradient may continuously change. This is commonly the case during semi-mountainous and mountainous stages which are often conducted at moderate altitudes. Indeed, AWC models do not appear to be very accurate when examined at altitude (202). Future AWC models may need to account for the change in task demands (and CP) observed as a result of changes in gradient.

From Study Two it is unclear if the greater power output observed over long durations in semi-mountainous and mountainous stages was because of tactics, race dynamics, the time spent on climbs or if cyclists produce greater power output while riding up an incline. Study Four aimed to investigate the association between road gradient and MMP in professional male road cyclists during mountainous stages from a grand tour event. The MMP produced over varying gradients was determined using averages from successive 5 s to 3600 s time periods of the entire event (Figure 8.2). However, there were several flaws with this analysis. Firstly, flat and some semi-mountainous stages did not contain any road gradient values greater than 5%. This meant that the majority of power output values in the greater than 5% power output band were only from mountainous stages. Secondly, no period of time of more than 600 s at gradients of greater than 5% could be found. This is because no time during a tour is spent longer than 600 s at a constant gradient greater than 5%. Interestingly, decents (<0%) appear to have higher 1 to 60 MMP compared with accents (0 to 5% and >5%). Higher MMP when cycling downhill may be due to the short sharp increases in power output when accelerating out of corners. Clearly, mountainous stages have the greatest changes in road gradient. Study Four examined the 1 and 5 min (60 and 300 s) MMP outputs from mountainous stages during grand tour events. It was hypothesised that the steeper the road gradient (-5 to +5%), the greater the average 1 and 5 MMP.

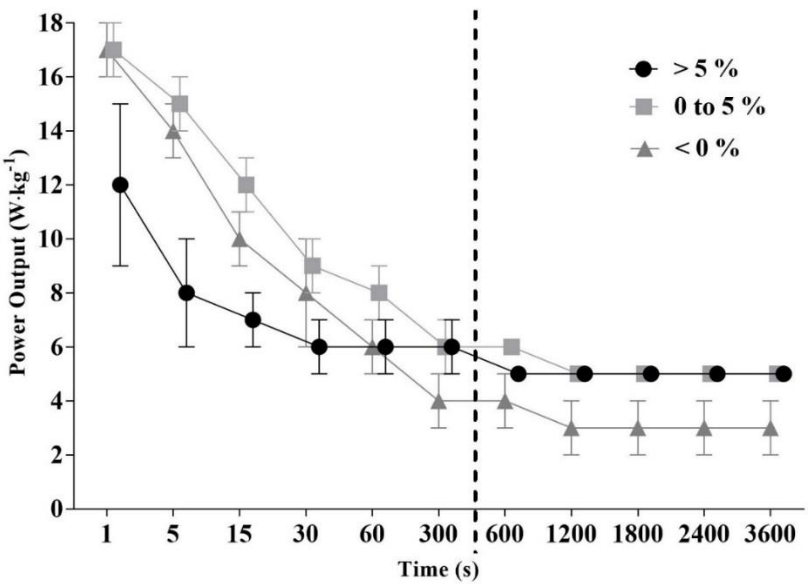

Figure 8.2: Attempted MMP curve from thirteen professional road cyclists using three gradient based power output bands during a grand tour.

Study Four found that the steeper the road gradient, the greater the average power output for both 1 and 5 MMP (Table 6.1). The reason for these results could be due to an array of factors including altered tactics, changes in cycling biomechanics, muscle requirement and cycling efficiency between uphill and flat cycling. A change in the biomechanics of cycling uphill allows for greater hamstring activation and a more even torque distribution throughout the pedal. The change in muscle recruitment influences the metabolic cost of uphill cycling causing a decrease in efficiency. With a decrease in efficiency, exercise capacity and, therefore, performance should be lower. Regardless of the greater metabolic cost, power output at both 1 and 5 MMP increased with steeper gradients (Table 6.1).

In Study Three, the UPHILL CP test was conducted at a road gradient of 6.2 ± 1% (Figure 5.3). Road gradients greater than 6%, similar to Study Three, were unavailable in Study Four because grand tours do not have sections of the race greater than 6% road gradient. The greatest road gradients available from grand tours in Study Four were 5% for 1MMP and 4% for 5MMP. Study Four provides slightly more detail on the influence of gradient on external workload demands during competition. The reasons the observed power output remained the same are multiple and mechanistic including biomechanical position, cadence, gross efficiency and alternative muscular recruitment patterns.

Within the initial chapters of the thesis power output was examined over a single (Study One), multi-stage (Studies Two and Three) and grand tour events (Study Four). Within the cycling literature little is known on external workload demands over a longitudinal period. Therefore, Study Five aimed at describing the within-season external workloads of professional male road cyclists. Specifically, Study Five monitored four professional male road cyclists for 12 months in preparation for the world team time trial championship. The volume (distance and time) and exercise intensity were measured overall and between training and racing in three defined macro cycle phases (Table 7.2) and week-by-week (Figure 7.2). Study Five provides coaches, practitioners and enthusiasts with an insight into the external workload demands of professional road cyclist’s preparing for the world team time trial. Using three coach defined macro cycle phases, external workload was found to dramatically shift throughout the season.

Although not reported in Chapter Five, the changepoint analysis used in Study One confirms the three distinct macro cycles determined by team coaches. Indeed, the training and racing duration and distance data from figure 7.2 in Study Five were reproduced and analysed using changepoint analysis (Figure 8.3). Changepoint statistically defined the three largest changes in duration and distance for training and racing over the whole season. Figure 8.3 demonstrates that the changepoint analysis was able to resemble the three macros cycle phase’s as described by the coaches. From the data it can be assumed that riders were accurate in achieving their specific external workload phase plans and that changepoint analysis can be used for the longitudinal analysis of workload in sport and exercise science research.

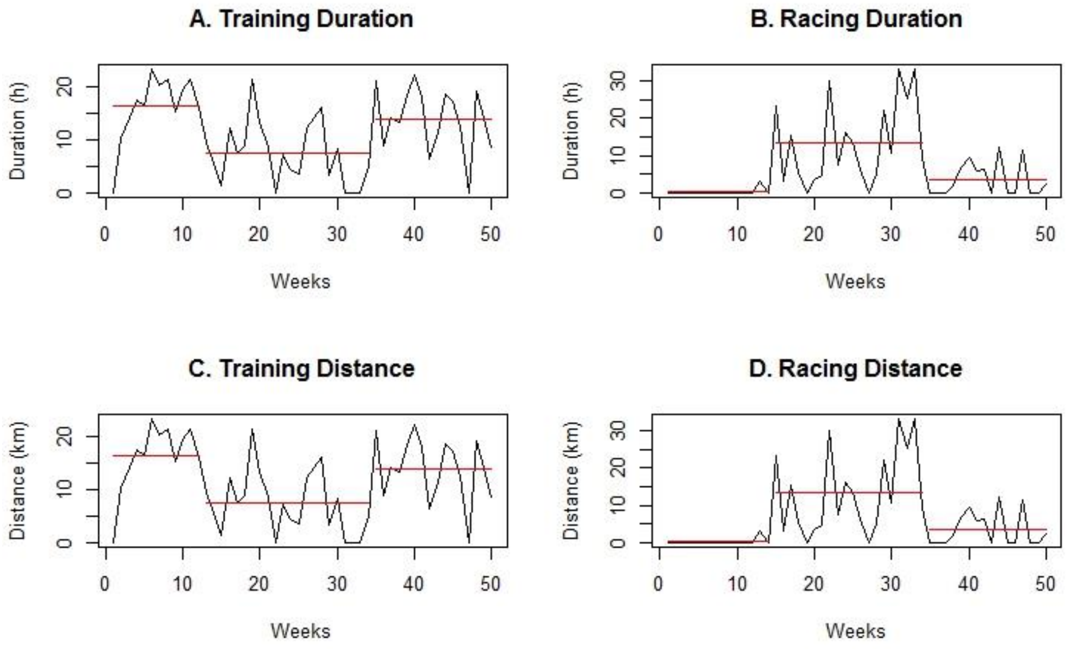

Figure 8.3: The duration and distance for training (A, C) and racing (B, D) analysed using changepoint analysis.

The findings from Study Five indicated that volume and intensity significantly differed between training and racing over each of the three distinct within-season phases. In short, the off season (phase one) was clearly identified with a significantly lower volume and intensity compared with phases two and three (Table 7.1 and Figure 7.1). Also, the weekly volume and intensity differed between training and racing (Table 7.2 and Figure 7.2) Study Five provides a rare and brief insight into within-seasonal training and racing differences in professional male road cyclists. While training theory and periodisation are relatively well understood, little data has been published reporting the actual practice and external workload demands of professional road cyclists. Ultimately, the lack of peer-reviewed studies investigating the longitudinal practices is likely due to the reluctance of professional male road cyclists willing to release long periods of power output data and maintaining regular up-to-date records. Furthermore, the majority of data describing external workload demands in cycling were from an era known to involve doping and as such, the findings from this study provide a more recent overview of the seasonal external workload demands in cycling.

8.2 Practical Implications

The outcomes of this thesis enhance current understanding of how to analyse external workload data in cycling. A new technique for data analysis has been explored using changepoint (Study One). Additionally, the influence of topography and road gradient on external workload demands during professional road racing has been extensively examined. While these new potential techniques are not designed to replace existing ones, they are intended to aid the analyser in providing accurate feedback to the rider and enhance understanding in professional road cycling.

This thesis also employed conventional techniques currently used by professional road cycling teams and enthusiasts to analyse power output data including MMP (Study Two), CP (Study Three) and the percentage of power output in time bands (Study Four and Five). These were examined over varying topography categories and rider specialities. An accurate understanding of how topography categories and rider specialities influence this analysis should be undertaken when interpreting power meter data. Indeed, this thesis demonstrates that these factors are likely to influence the power output of cyclists and thus influence current methods used within cycling power analysis. It is recommended that estimated CP is measured on differing topographies (i.e. flat vs. uphill). For modelling CP, specific topography values are used to provide a more accurate estimation.

Overall, the data used in this research are rare, especially in the sense that they are drawn from two professional male road cycling teams. This thesis provides a brief insight into the demands of professional male road cyclists from within a stage, across a multi-stage race, a grand tour or throughout a whole season. This thesis also demonstrates the importance of monitoring and developing procedures undertaken by professional cycling teams so that these can be understood and used by amateur enthusiasts.

8.3 Limitations

The outcomes of this thesis have important practical and theoretical applications. However, some limitations apply. Firstly, the SRM power meter is a validated and reliable power meter (Table 2.2) for collecting field-based power output data. However, some riders collected their recordings and downloaded data post ride. Power meters were not always used during stages, specifically in Study Five and were not always working during each ride. Secondly, where available, data have been converted from absolute power to relative body mass power. Body mass data was not always available and when available, not always regularly measured. Finally, all studies within this thesis present field-based data. We have to be cautious when interpreting field-based data as multiple environmental factors including temperature, humidity and wind resistance will influence measurements. However, measurements provided in this thesis represent the real-world demands of professional male road cycling. Conversely, the laboratory is an indoor environment and fails to represent a real-world environment.

8.4 Directions for Future Research

Despite the findings presented, several practical and theoretical questions related to power output and cycling analytics remain. Firstly, future research should investigate the application of time series based analysis such as changepoint as addressed in Study One and in the general discussion. Secondly, the influence of gradient on critical power should be investigated further and tested at sea-level and mechanistically within a laboratory environment. Thirdly, studies should investigate other external factors which could influence power output measurements such as altitude, heat and wind resistance.

8.5 Conclusion

In summary, this thesis examined multiple factors which influence power output as a measurement of external workload on single and multi-stage cycling performance in professional male road cyclists. This thesis also examined the current methods used in analysing external workload data and investigated multiple methods in improving this process. This thesis concludes the following:

1) Power output is stochastic and can be modelled over time using a variety of time series analysis techniques such as changepoint (Study One).
2) Caution should be taken when interpreting MMP and CP values (Studies Two and Three). External environmental factors including topography, road gradient and rider speciality appear to affect these measurements.
3) Road gradient changed estimated CP (Study Three) as well as 1 and 5 MMP output during grand tour mountainous stages (Study Four).
4) The external workload in professional male road cyclists varies during the season (Study Five).

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