Quantification and description of braking during mountain biking using a novel brake power meter

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Student Declaration

I hereby declare that this thesis is my own work and does not, to the best of my knowledge, contain material from any other source unless due acknowledgement is made. This thesis was completed under the guidelines set by Massey University's College of Health, for the degree of Doctor of Philosophy and has not been submitted for a degree or diploma at any other academic institution.

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Date: ____

Foreword

When I came to New Zealand to do my PhD, I wasn't very sure of what I wanted to study. I knew I wanted to study mountain biking, but it's such a diverse sport with many genres, and I really had no clear direction of where my studies would go. However, one thing was for sure: I was in the right place!

My supervisory team had what I felt was a good mixture of specialities within Sport & Exercise Science, and the further I went through my research, the more I understood the perfect mixture of talent surrounding me. Strangely, while this same team had previously paved the way to new ideas in mountain biking research, I was given full liberty to shape my own ideas and make my own mistakes.

The brake power meter idea was born during an actual mountain bike competition. I found myself racing against my supervisor, Steve, who was much more fit than myself. As we continued the race and I could hear Steve's squeaky brakes, I knew the only reason I was able to keep up with him was for not braking myself.

Rather than being told it was a silly idea to measure braking for my PhD, I was taught how to apply for funding, given advice on what kind of variables we should measure, and had conversations on how we might run experiments. It was these kinds of events that taught me the depth of expertise and highly innovative scientists I'm surrounded by.

I've been tested more than I ever expected throughout this process, but have gained knowledge and experience beyond that of sports experiments.

Thank you for believing in me.

Acknowledgements

Thank you to my family and friends for motivating me and assuring me that this process will be worth it in the end. GUNAX LBH GB ZL FGVAXL.

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This is for the haters.

Publications & Presentations

Publications

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Conference Presentations

Matthew C. Miller, Philip W. Fink, Paul W. Macdermid, Steven R. Stannard (2017). The utilization of a bicycle brake power meter for cross-country mountain biking. Australian Strength and Conditioning Association, Gold Coast, Australia, 10-12 Nov

Matthew C. Miller, Paul W. Macdermid, Philip W. Fink, Steven R. Stannard (2016). Performance and physiological effect of different pacing strategies for mountain bike racing. European College of Sports Science, Vienna, Austria, July 9

Matthew C. Miller, Chad A. Witmer, Gavin L. Moir, Shala E. Davis (2014). The Predictive Validity of Critical Power and Functional Threshold Power for Mountain Bike Race Performance. Tsukuba Summer Institute, Tsukuba University, Japan, July 23

Matthew C. Miller, Chad A. Witmer, Gavin L. Moir, Shala E. Davis (2014). The Predictive Validity of Critical Power and Functional Threshold Power for Mountain Bike Race Performance. ACSM Annual Meeting, Orlando, FL, USA May 27-31

Emily J. Sauers, **Matthew C. Miller**, Benjamin Sina, Bryce J. Muth, Brandon W. Snyder, Shala E. Davis (2014). Effects of Full-fat and Fat-free Chocolate Milk On Recovery Following Endurance Running. ACSM Annual Meeting, Orlando, FL, USA May 27-31

Abstract

Olympic format cross country mountain biking is both physically and technically demanding. The demands of this cycling genre are in contrast to road cycling because of the demanding off-road terrain. With its many obstacles and different surfaces, riders must make their way up and over steep hills a number of times throughout a lap. It's very easy to be able to measure the performance of the riders on ascending sections of the track thanks to on-the-bike personal power meter that measure the propulsive work rates in the pedals. However, there is currently no commercially available method to assess the way the rider handles the bike on descending sections. This thesis first highlighted the differences in physiological demand of descending on off-road versus on-road (**Chapter 4**). An interesting finding in **Chapter 4** also showed that riders might be able to save energy by adopting a coasting strategy down hills. This caused the researchers to question the bicycle handling attributes that might allow this, which led to the development and validation of a device designed to measure how the rider uses the brakes while riding/racing (**Chapter 5**). From there, we completed an investigation akin to the early mountain biking descriptive studies (**Chapter 6**), but instead of focusing on data related to respiratory and metabolic load, the brake power meter was employed. The finding that braking patterns were related to mountain biking performance was not surprising, but being the first team to quantify this was very exciting. Since most of the braking was occurring on the descents in that study, we examined the differences in braking between training groups on an isolated turn (**Chapter 7**). The finding that inexperienced riders use their brakes differently—and that this results in reduced performance—left no doubt to the importance of braking. From there, we revisited the method used to calculate rear brake power, since current methods led to inaccurate measurement during skidding

(**Chapter 8**). This thesis culminated with the exploration of an algorithm that could quickly and easily describe mountain bike descending performance with one single metric (**Chapter 9**); the hope is that the normalized brake work algorithm should increase the utility of the brake power meter for training purposes and post-competition performance analysis. Overall, this thesis highlights the need, importance and utility of a bicycle brake power meter to assess mountain bike performance.

List of Abbreviations

ANOVA – analysis of variance

AT – aerobic threshold

CP – critical power

DH – downhill (descending) terrain

E_K – kinetic energy

F - force

FTP - Functional threshold power

HR – heart rate

I - inertia

IP – intermittent power

J - joule

LT – lactate threshold

FLAT – flat terrain

m – meters

ω (omega) – angular velocity

OBLA – onset of blood lactate

r - radius

RCP – respiratory compensation point

rad - radians

RMS – root mean square

s - seconds

SD – standard deviation

t – time

τ - torque

TRIMPS – training impulse

UP – uphill (ascending) terrain

v - velocity

VO_2 – volume of oxygen uptake

W – watt

W^1 – anaerobic work capacity

XCO-MTB – Olympic format cross-country mountain bike racing

Table of Contents

List of Figures

List of Tables

Chapter 1

INTRODUCTION

Indices to predict sport performance have largely relied on results of field and laboratory tests due to their ease and reliability of measurement (Miller *et al.* 2014). Data garnered through these tests has led to fine-tuned physical training programs for athletes and has arguably contributed to the trajectory of world records throughout sporting history (Clarke & Skiba, 2013). While beneficial overall, the laboratory focus has overlooked the dynamic and technical nature of some sports, specifically in Olympic format cross-country mountain bike racing (XCO-MTB).

XCO-MTB presents unique challenges compared to laboratory or road cycling, mostly relating to the undulating terrain and variable surface conditions on mountain bike tracks. While 40% of race distance might be uphill (Impellizzeri *et al.* 2007), races no longer feature one major ascent and descent; rather, the terrain is generally made up of multiple short, steep ascents separated by short, steep descents in succession throughout a lap. Clearly this is at odds with traditional steady-state laboratory correlates traditionally used in testing protocols. The sort of track profile in XCO-MTB requires intense intermittent bouts of propulsive power production on ascending segments, with recovery bouts occurring on the descents (Macdermid & Stannard, 2012). However, physiological demands are complicated by the uneven and variable riding surfaces, which can exacerbate oxygen demand due to the need to recruit additional musculature for vibration damping (Macdermid *et al.* 2014; Macdermid *et al.* 2015). This in turn reduces the ability to recover during non-pedalling bouts (Macdermid *et al.* 2017). These external variables lead to relatively steady and elevated heart rate profiles, despite high oscillations in power output (Stapelfeldt *et al.* 2004). Attempts to reduce the magnitude of the dissociation between work output and physiological response has garnered much research attention lately as scientists seek to utilise advances in technology for the athletes' benefit (Hurst *et al.* 2017; Macdermid *et al.* 2015; Macdermid *et al.* 2017).

Early reviews of the XCO-MTB have indicated that there is a need to quantify the way a rider negotiates terrain (Impellizzeri *et al.* 2007) due to the notion that this has some effect on performance. Broadly termed 'technical ability', it has been noted that some riders can increase their speed on descending sections of the track to make up for lost time on ascents (Mastroianni *et al.* 2000). While this raises particular health and safety concerns (Aleman *et al.* 2010), small differences in technical ability can be crucial for performance in XCO-MTB, though this area remains unexplored.

The programme of research described in this thesis aims to ascertain the need and utility for technological developments to better understand dynamic XCO-MTB performance. These aims evolved after particularly interesting findings in the first experimental chapter (**Chapter 4**), which identified the need for a device to quantify mountain bike descending ability. Successive investigations indicated the validity of a purpose-built, novel brake power meter (**Chapter 5**), highlighted the enhanced understanding of XCO-MTB by collecting variables recorded with the brake power meter during simulated racing

(**Chapter 6**), explored controlled and isolated aspects to better understanding of braking variables (**Chapter 7**), explored a method to correct shortcomings of the device (**Chapter 8**) and finally, reduced braking performance to a single metric designed to predict descending performance (**Chapter 9**).

The experiments presented in this thesis pioneer the way toward the development of novel devices for cycling performance analysis, ultimately culminating by explaining new, complicated variables with easy-to-understand metrics. Findings are presented as stand-alone research manuscripts which are published or in-review, then compiled within this thesis as a complete program of research towards a Doctor of Philosophy qualification.

Chapter 2

REVIEW OF LITERATURE

2.1 Demands of Olympic format cross-country mountain bike racing

Competitive cross-country mountain biking is recognized by the International Olympic Committee (IOC) and was first held during the Atlanta games in 1996. Current XCO-MTB racing is governed by the Union Cycliste Internationale (UCI), which rules that competitions should last approximately 90 minutes (Stapelfeldt *et al*. 2004). To make up the race duration, relatively short (4-9 km) circuits are completed a number of times on a mixture of terrain that is mostly off-road (Lee *et al.* 2004). The terrain can feature a number of obstacles including roots, rocks, jumps and drops which can be natural or man-made and on flat, ascending or downhill terrain (Figure 2.1). Riding surface can be weather-dependent, meaning that a hard-packed, dry and dusty course could become muddy and slippery after a rain; however, by and large competitions go on as scheduled during inclement weather, with only minor changes made to the number of laps so as to stay within completion time restraints. Tracks may also feature grass, gravel or tar-sealed road sections, and it is expected that top athletes be able to navigate any type of terrain in expert-fashion.

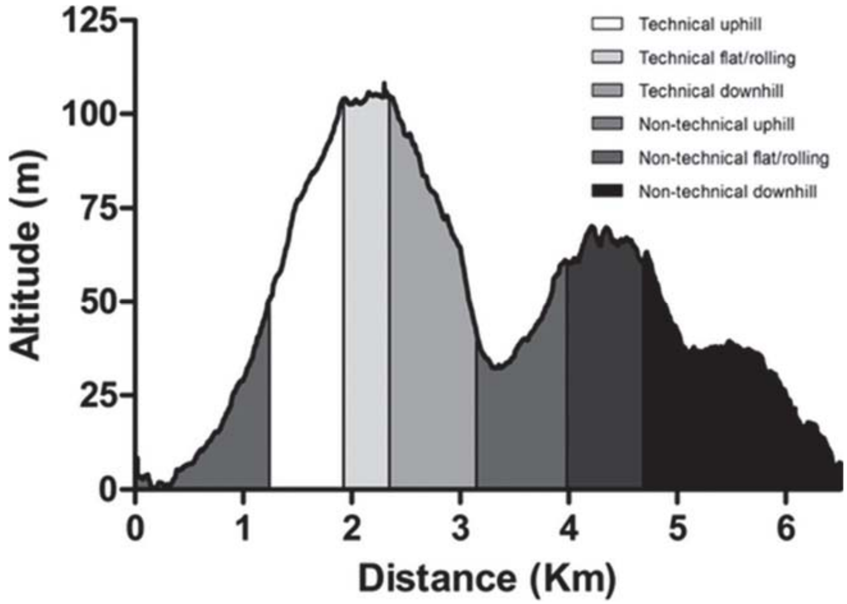

Figure 2.1 Elevation profile of the XCO-MTB World Championships in Canberra, Australia in 2009 was originally published by Abbiss *et al*. (2013).

Races are mass-start, but quickly funnel into sections of track that are only one-rider-wide, which makes passing difficult (Macdermid & Morton, 2010). The 80% rule used in Elite racing governs that any rider who falls to below 80% of the pace of the fastest rider will be pulled from the race. This was made to reduce lapped traffic for the front competitors, but complicates race strategy for racers lining up in the back of very large (100+) rider fields (Macdermid & Morton, 2010). As such, race dynamics demand an all-out effort from the start to gain positional advantage before the first narrow section of track, after which intensity quickly reduces to a more sustainable effort (Viana *et al.* 2013). Despite this all-out start, elite riders are able to maintain lap time across the duration of the lap regardless of variation of speeds recorded in different parts of the track (Martin *et al.* 2012). Thus far this lap time maintenance stands as a testament to their peak physical capability. As expected, ascending portions are the slowest parts of the track, with technical ascents being even slower (Martin *et al.* 2013). Some 40% of the race distance could be ascending (Lee *et al.* 2002), which is course dependent. Analysis of the 2009 XCO-MTB World Championships revealed 168 m of elevation gain in every 6.47 km lap (Abbiss *et al.* 2013). These observations place a premium on ascending ability, which demands a high power:weight ratio (W/kg) (Gregory *et al.* 2007).

The earliest descriptive study by Impellizzeri *et al*, (2002) observed that 82% of lap time was spent above the lactate threshold (LT), which highlighted the intense nature of the sport. In this study, riders maintained 90% of maximum heart rate (HR) for the duration of the race, which corresponded with 84% of maximum oxygen uptake ($\dot{V}O_{2max}$) measured in laboratory testing. Generally, HR recordings appeared to remain steady in the vicinity of the LT throughout races, which was supported by the relatively high levels of blood lactate measured during competitions (Impellizzeri *et al.* 2007). The LT had already been well-accepted as a strong indicator of endurance and road cycling ability (Sjodin *et al.* 1981; Coyle *et al.* 1991), and race-specific data tended to support its importance for XCO-MTB performance. While this may have been the case, the literature fell short of describing the demands of XCO-MTB in comparison with road cycling until the advent of on-the-bike personal power measuring devices (power meters); to that point XCO-MTB was considered to be equivalent to a shorter, intense road race (Fernández-García *et al.* 2000). Some years later, these early studies were revisited with the addition of power meters, and later, portable breath-by-breath $\dot{V}O_2$ analysers, which increased our understanding of the uniqueness of XCO-MTB.

In 2004, Stapelfeldt *et al*. published the first longitudinal analysis of power profiles from XCO-MTB competitors, indicating that average power output was relatively high (3.6

W/kg for males) throughout a season's racing. The authors noted that 22% of power produced during XCO-MTB was supramaximal, which alerted sport scientists to the sport's variable intensity. Power profiles from XCO-MTB races were contrasted with cyclocross races (Hansen *et al.* 1999). The authors noted that XCO-MTB race duration likely contributed to overall lower power output when compared with cyclocross racing (where XCO-MTB is slightly longer in duration), placing the intensity somewhere between cyclocross and road cycling with respect to demands. Nevertheless, it was confirmed that periods of high power output (250-500 W) were seen on ascents, which lasted several seconds to several minutes, and that power output was lowest on descents. Macdermid & Stannard (2012) were the first to include respiratory gas analysis in their comprehensive study on the demands of XCO-MTB. HR and power readings reverberated previous work, but the authors additionally highlighted that *actual* measured VO_2 equated to be 77% of maximum values recorded in an exhaustive laboratory test. Throughout these later studies, it became clear that there was a phase-delay between actual propulsive power created through pedalling and the physiological strain placed on the rider, especially on descending sections (Figure 2.2).

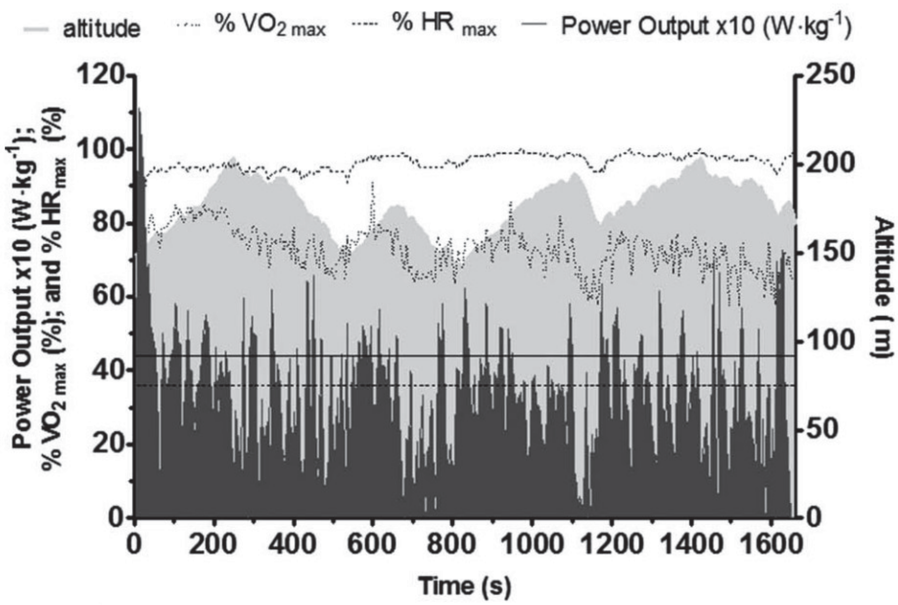

Figure 2.2 Elevation profile, propulsive power output and physiological variables (heart rate and VO_2) from one individual during a simulated XCO-MTB race. This figure appeared in Macdermid & Stannard, 2012.

The group of Hurst *et al*. (2006) were the first to explore the demands of downhill riding, and noted that the additional work of the upper body contributed to an elevated physiological strain in contrast with power output. Later studies investigated specific attributes of XCO-MTB riding surfaces, and indicated that the body adopts an autonomic strategy to reduce vibration exposure to the head and central nervous system (Macdermid *et al.* 2014). The bike and axial body are exposed to high frequencies and magnitudes of vibrations during simulated XCO-MTB racing (Figure 2.3), however musculotendonous damping and eccentric contractions reduce exposures before reaching the head and lumbar spine; this damping comes at an increased physiological cost when compared with road cycling (Macdermid *et al.* 2015). It has been postulated that vibration exposure—and thus damping requirements—increase linearly with velocity, which contends that the increases in both speed and damping requirement within descending track segments may explain increased physiological strain. Exacerbated oxygen demand has shown significant reduction in cycling economy on downhill sections when compared with ascents, and may reduce the rate of recovery between high-intensity ascents. Researchers have indicated the need to investigate strategies to reduce oxygen demand on descents to help improve overall performance (Macdermid *et al.* 2016), however attempts to do so have not been realised.

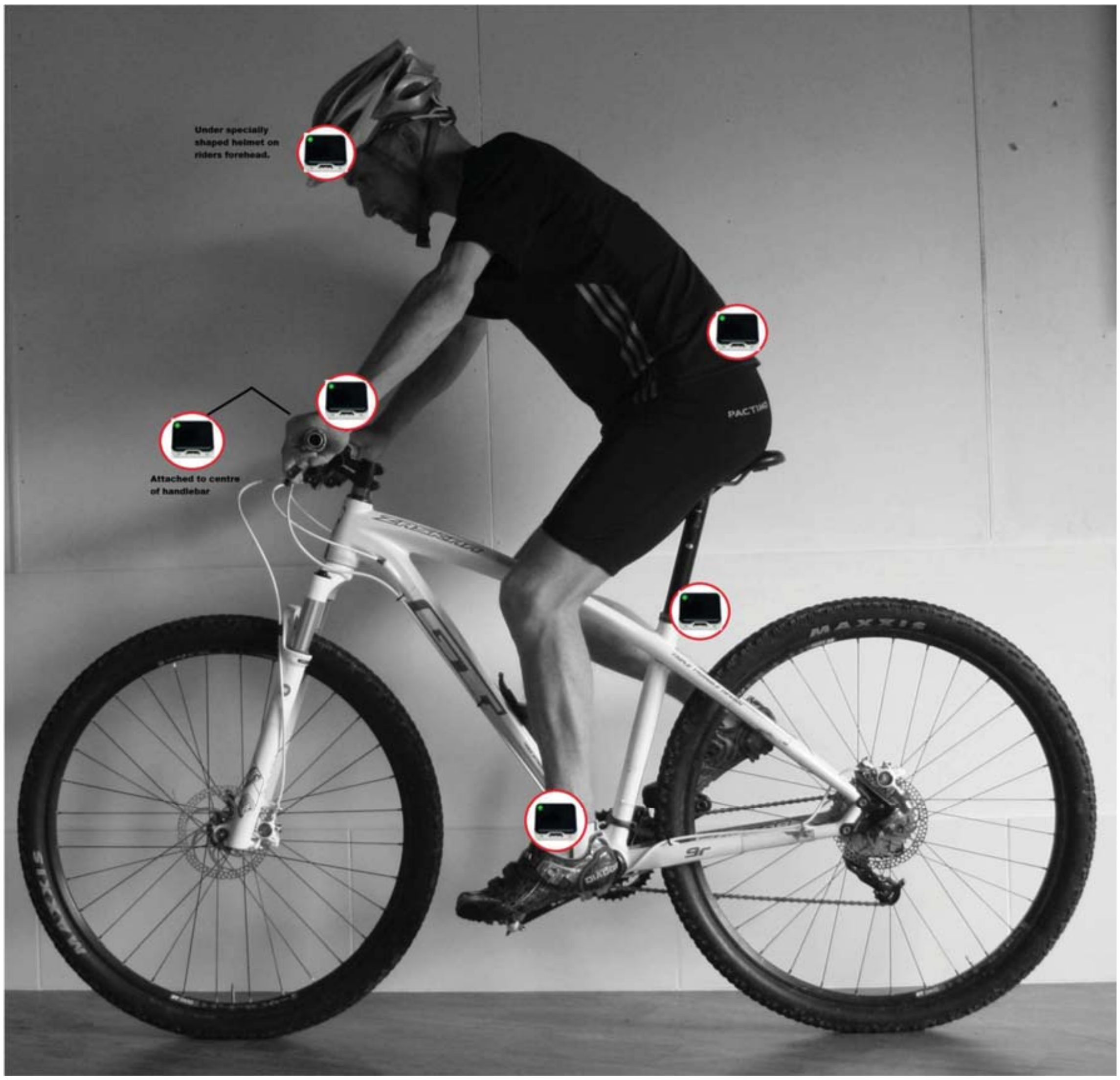

Figure 2.3 Example of placement of accelerometers for use in measuring vibrations during cycling. This photo was first published by Macdermid *et al*. (2014).

2.2 Indices of performance

To date, much of the literature related to XCO-MTB has focused on finding the strongest indicator of actual performance measured from laboratory or field tests. The goal of this type of research is to identify attributes or indices separating the best performer from the least performers, and to henceforth utilise training interventions to improve these attributes/indices. As highlighted above, descriptive characteristics of XCO-MTB stalled for some years while scientists searched for additional variables to measure, and these predictive tests appear to be following a similar trajectory. The traditional exhaustive cycle ergometry test has proven to be popular, with different studies investigating various metabolic thresholds and correlating them with actual or simulated XCO-MTB performance. Amongst these it became clear early on that power output at the ventilatory thresholds on the lower end of the intensity spectrum were not suitable determinants of performance ($r=-0.37$) (Impellizzeri *et al.* 2005). VO_{2max} proved to be slightly better ($r=-0.46$), which is to be expected due to the very high oxygen uptake values previously recorded in XCO-MTB athletes during maximal testing (Impellizzeri *et al.* 2002; Impellizzeri *et al.* 2005). High-intensity testing continued to show promise with later investigations supporting the strong relationship with maximum power output (Costa *et al.* 2008). However, results from these tests overlooked the aerobic nature of the sport and lacked practical resolution because after all, they were completed in the laboratory and not in the field.

By further analysing respiratory gas and metabolite concentrations, high-end aerobic metabolic thresholds in the vicinity of the LT and anaerobic threshold (AT) have repeatedly been shown to relate to strongly to performance and thus continue to be some of the better laboratory indices. Relative power output (W/kg) at the respiratory compensation point (RCP) was one of the first strong significant indicators of performance (r=-0.61) (Impellizzeri *et al.* 2005). That original data was supported by a small study reporting a significant relationship with performance time and the second LT (Costa *et al.* 2008). The findings of Gregory *et al*. (2007) reinforced this, highlighting that relative power output (W/kg) at the individual anaerobic threshold were significantly associated with a simulated XCO-MTB time trial (r=-0.78). In this same study, the researchers went further and looked purely at ascending performance, which was similarly strong (r=-0.75). Furthermore, it was uncovered that these relative power output values were stronger indices than absolute measures due to the effects of gravity on ascending. Prins *et al*. (2007) noted that relative power output at the onset of blood lactate (OBLA) was significantly related to an XCO-MTB-specific time trial (r=-0.74). This was followed up some years later (Miller *et al.* 2014), with the authors indicating that the functional threshold power (FTP) field test used to estimate power output at OBLA (Gavin *et al.* 2012; Allen & Coggan, 2012) was significantly related to race performance (r^2=0.74), which was a successful bid to determine widely available and convenient testing methods (Miller *et al.* 2014). In an exploratory study, Miller *et al*. (2015) later suggested that relative critical power (CP) may strongly indicate XCO-MTB performance since it demarcates the boundary between aerobic and anaerobic energy production, however the concept has yet to gain momentum in the sport.

The majority of these predictive studies have focused mainly on well-known steady-state aerobic or peak anaerobic values, which arguably overlooks the numerous intense periods within competition. While specific stationary XCO-MTB time trial performance is strongly related to actual performance (r=0.79) (Prins *et al.* 2007), this type of test is more difficult to measure than laboratory variables, and could be dependent on the course profile. Attributable to the intermittent nature of XCO-MTB, mean power throughout a 5 x 30 s Wingate was shown to indicate performances quite well (Inoue *et al.* 2012). Following these measurements, researchers developed a novel intermittent field testing protocol (Miller *et al.* 2014), noting that it predicted performance better than the FTP field test and could be completed in 20 minutes on a stationary trainer, which is appealing in its own right.

Table 2.1. These regression models were derived from Miller *et al*. (2014) and indicated the strength of cycling field tests for XCO-MTB race prediction.

Variable	Model	r	r^2	MSE	Error
Relative FTP	Race time = 6317.224 + (-655.688 Relative FTP)*	0.858	0.736	92,190	303.6
Relative IP	Race Time = 6662.768 + (-598.752 Relative IP)*	0.886	0.786	74,773	273.5

Note: Relative FTP = Functional Threshold Power; Relative IP = Intermittent Power; MSE = mean square error, calculated as the residual sum of squares divided by the degrees of freedom; Error = estimation error, calculated as the square root of MSE.

* Both models $p < 0.001$

Promising new methodology incorporating multidimensional variables has further enhanced knowledge of XCO-MTB performance indices (Novak *et al.* 2017). Incorporating video footage from XCO-MTB trails, participants were timed on their ability to choose the fastest section of trail. Results from this test were henceforth utilised in various regression models, and highlighted that a combination of fitness and sport-specific decision-making variables could predict performance better than unidimensional models. However, these models were admittedly weakest when predicting technical and/or downhill sections.

To date, little research has focused on predicting ability on downhill sections within XCO-MTB, with research relying on the few descriptive studies on descending performance. This type of research is important because there is an equal amount of elevation gain and loss due to the lap-style format of racing. Recreational participation in downhill mountain biking is physically demanding and has been likened to other moderate intensity exercise, with the magnitude of increase in oxygen uptake and heart rate likened to off-road motorsports (Burr *et al.* 2012). However, competitive outcomes are not reliant on propulsive power output (Hurst *et al.* 2006). In both types of riding, there are similarly notable reductions in handgrip strength due to fatigue, and additional energy that is potentially being directed towards concentration. The variation in descending performance has been suggested to be attributable to difference in technical ability (Mastroianni *et al.* 2000), which was supported by qualitative analysis (Chidley *et al.* 2014), though reports otherwise remain unquantified. It seems sensible to begins to describe or quantify descending performance—especially given the relative weakness of physical fitness indices—however, the technology to do so is not currently available. It is possible that these types of analyses may allow better identification and resolution of factors that performance.

2.3 Performance analysis and technological tools

The efficacy of training interventions has reliably been monitored by collecting variables such as oxygen uptake, the rate of substrate utilisation, and HR and comparing them to the rates of work done in the laboratory on cycle ergometers. To monitor training sessions, athletes and practitioners adopted metrics such as the training impulse score (TRIMPS) (Banister *et al.* 1985)—which accounted for exercise time above and below the threshold heart rate—to gain a better understanding of the stress from each session. This model has been adapted over time to weight high-intensity training and differences in sex characteristics (Morton *et al.* 1997). While these models are not perfect, the ease of collection and calculation—along with the easy-to-interpret single metric—have proven this metric to be valuable.

As technology advanced, the advent of on-the-bike personal power meters (Figure 2.4) has revolutionised cycling, allowing training and race data to be collected and monitored across days, months and multiple seasons. To calculate propulsive power, pedalling torque and the angular velocity of the pedals are multiplied, given:

$$\text{Power} = \tau * \omega \qquad \text{(Eq. 2.1)}$$

Where, τ is torque, and ω is angular velocity. The unit for power is the watt (W). Typically, average power output is of interest, and it would be up to the coach or practitioner to decide the time interval of interest.

The total mechanical work done is calculated as the product of average power and time, given:

$$\text{Work} = Average\ power * \text{t} \qquad \text{(Eq. 2.2)}$$

Where, t is the duration (s). The unit for work is the joule (J).

These measurements are reflective of the rate of energy expended for pedalling through a race or section, which is valuable to the coach for understanding training/competition stresses. These measurements help the coach to guide training interventions aimed at improving performance. To this point, measuring propulsive power output has become extremely well-accepted in cycling, mainly due to its ease of collection and strong association with physical fitness (Jobson *et al.* 2009). This has led to a number of practitioner publications that put readings of power output into an easy-to-understand context for greater utility of data (Allen & Coggan, 2012). An effect of this has been the increasing availability of companies marketing these types of tools; to date there are over a dozen manufacturers marketing propulsive power meters.

Figure 2.4 Example of a functional (albeit dirty) propulsive power meter located within the chainring spider of a mountain bike crank set.

One area that remains debated is the accuracy and validity of devices marketed by different power meter manufacturers (Abbiss *et al*, 2009; Bertucci *et al.* 2005; Millet *et al.* 2003; Novak *et al.* 2015; Sparks *et al.* 2015). The SRM power meter is often considered the ‘gold standard’ of commercially available power meters (Hurst *et al.* 2015), which may be attributable to its longevity within the market. This device places strain gauges and accelerometers within the crank’s chainring spider to calculate pedalling torque and angular velocity, respectively, and it has long been used to compare the data collected from devices made by competing manufacturers. Nevertheless, despite the various placements or methods utilised to calculate both torque and angular velocity, algorithm development has allowed devices to attain similar readings (Gardner *et al.* 2004) regardless of the configuration the electronics are placed. This was of particular interest at the onset of the present research program; therefore, we undertook the investigation of three makes of power meters during both steady and XCO-MTB riding (Appendix I). This investigation concluded that power meters are equal during steady riding, but small differences arise during field use due to different technologies utilized to measure cadence. It has been surmised that the low error in these devices can reflect the small changes that affect performance in road cycling, and thus the propulsive power data collected remains highly regarded (Paton & Hopkins, 2001).

The development of easy-to-understand metrics from propulsive power meters continued on from heart rate models. This has included the complicated Impulse-Response model (Busso *et al.* 1994; Morton, 1997), which calculates training stress curves and allows an easier understanding or prediction of longitudinal training stresses. Other scientific models, such as the critical power and W'_{bal} model (Clarke & Skiba, 2013) have proven useful to calculate physiological reserves within training and racing situations to allow optimal pacing strategy. At the same time, coach practitioners have taught various additional models to predict peak performances and guide training (Allen & Coggan, 2012), however despite their wide acceptance these have yet to be fully accepted in the scientific community. Nevertheless, these single metrics help increase the utility and efficacy of power meters as training tools.

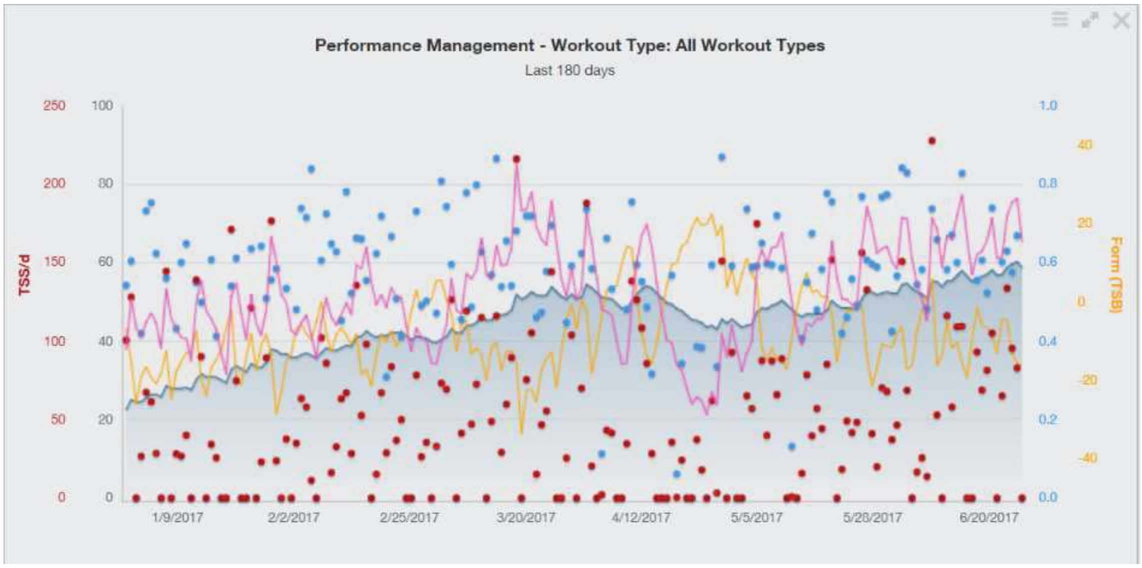

Figure 2.5 Some of the cycling metrics used by cycling practitioners presented from TrainingPeaks software. It is not expected that all this data is useful to the untrained eye.

At the same time, it is common for other types of simple data analyses (Stannard *et al.* 2015), even though not all have yet to be dissected in the literature. An example of some the metrics coaches may view can be seen in Figure 2.5. More common/well-accepted practices for power data analysis include: the visual inspection of data; normalization of power output (Allen & Coggan, 2012; Jobson *et al.* 2009); frequency histograms based on intensity zones; comparison of HR and power output over a time course or after repeating sections of a lap; detection of bilateral pedalling asymmetries (Carpes *et al.* 2010); and analysis of pacing strategy within races and training. The aforementioned analyses have allowed coaches and athletes the ability to fine-tune training and racing programs for peak physical ability

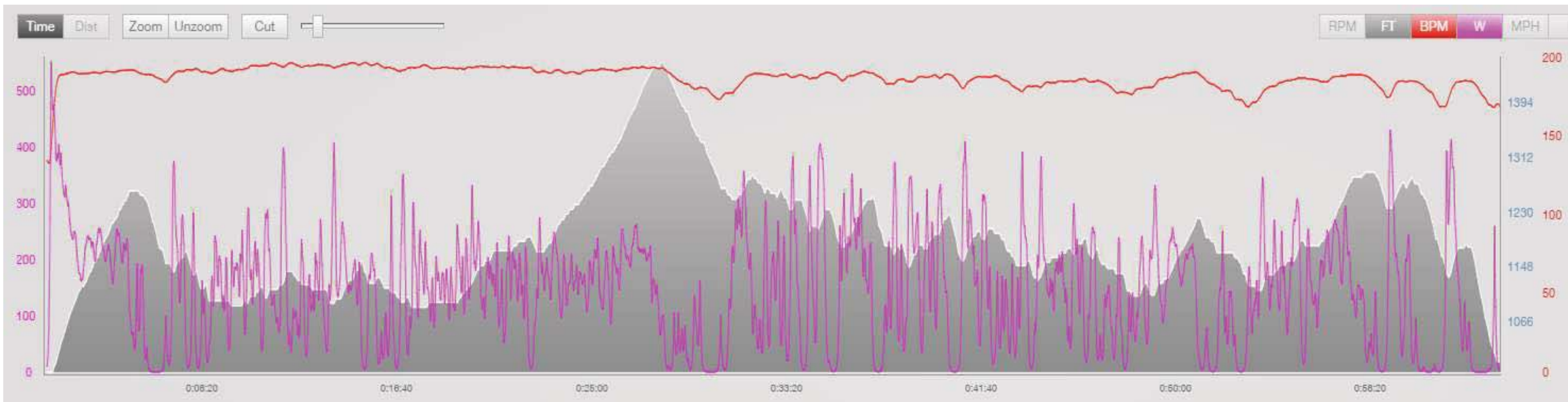

Figure 2.6 Power (W; pink), heart rate (BPM; red) and elevation (Feet; grey) collected from one competitive cyclist during actual racing using TrainingPeaks software.

These types of analyses have similarly become well accepted to fine-tune XCO-MTB performance (Macdermid & Stannard, 2012). An example of the analyses that can be completed can be seen above in Figure 2.6, which is a snapshot of real racing data from a competitive mountain biker. While the recordings from global positioning systems (GPS) lack finite resolution (Wing *et al.* 2005), a 'good enough' approach has been taken when analysing those types of data. As shown in the figure, coaches and athletes can view the elevation profile and corresponding power output; based on known physiological thresholds, HR and power data enhance understanding. Henceforth, the data can be used to determine strengths and weakness of individual cyclists, or to determine pacing strategy.

Figure 2.6 highlights the high power output at the start of the race, and a reduction is seen thereafter despite a relatively steady elevated heart rate. One indication this individual analysis may give is that the starting intensity was too high, which is clear due to the fact that this power output was never achieved in the remaining hour of racing. Perhaps by knowing the rider's physiological thresholds—such as power output at the lactate threshold—strengths or weaknesses may become apparent and can direct training interventions. For example, it very well may be that in this case the athlete was able to maintain power output at 100% of the lactate threshold on the track's longest ascent, which may be a personal best after 30 minutes spent racing. However, it could be the case that the short ascents in the later part of the race were far below what the athlete has shown possible in training. In these cases, adjustments could be made to training to focus on improving weaknesses.

One aspect of performance that is not apparent with current analysis tools is that of descending. It very well could be that this rider was only able to negotiate the descents on this track by getting off the bike and walking, then pedalling for short sections. This type of riding would be a serious detriment to performance because time would certainly be lost, however this is impossible to see based strictly on propulsive power meter data. Unfortunately, this type of analysis is difficult to quantify and thus left to guesswork.

2.4 Descending performance

As XCO-MTB race tracks roll through terrain, laps start and end in the same location. Accordingly, there are equal amount of elevation gain and loss, and thus similar amount of ascending and descending in a lap. However, ascending portions of the track are markedly slower as the riders compete against gravity, and because of this, over 40% of race time is spent ascending. Analysis amongst different groups competing on track has revealed that the best riders spend the least amount of time on technical ascents (Martin *et al.* 2012). GPS analysis has indicated that the majority of competition time is spent ascending on the track on various segments featuring a variety of steepness and technical demand (Abbiss *et al.* 2013). It is because of this that climbing ability has been indicated as the most important attribute for XCO-MTB race performance. While this is likely due to differences in physical fitness, it is in reference to these observations that recommendations have been made for riders to focus on technical uphill ability (Abbiss *et al.* 2013). It comes as no surprise then that most literature has focused on aspects that could explain or improve ascending performance.

However, most literature has overlooked the importance of descending ability, demand and performance, with only a few refereed papers covering the topic. It became apparent early on that descending on a mountain bike in itself was not dependent on propulsive work (Hurst & Atkins, 2006), but was rather related to aspects of technical ability (Mastroianni *et al.* 2000). The group of Chidley *et al.* (2014) took a qualitative approach to gain an understanding of descending ability, however this required visual inspection of actual riding by an experienced coach. Some of the earlier studies helped explain that the technical nature of the track can affect the recruitment of upper body musculature, supposed mainly for steering and postural work throughout descents (Hurst *et al.* 2013). Later studies indicated that vibrations translated from the riding surface through to the body of the rider were particularly high on descents, and may be attributed to the high speeds (Macdermid *et al.* 2014). These vibrations are dampened by the body through an autonomic strategy adopted to protect the central nervous system (Miller & Macdermid, 2015); largely done by tiny eccentric contractions, this vibration damping comes at a measurable metabolic cost. These reports helped fill the gap in understanding of why heart rate and oxygen uptake remained elevated in XCO-MTB, and further explains the dissociation between propulsive work and physiological strain in XCO-MTB (Macdermid *et al.* 2015).

As highlighted previously, researchers have understood well that descending performance contributed to overall performance—whether from the variations in time for competitors to complete these sections or due to the elevated physiological variables. Qualitative measures have not been able to answer all of the concerns, though they did reinforce the notion that propulsive power was not the answer to understanding these sections. A recent investigation by Macdermid *et al*. (2016), which highlighted very low cycling economy on descending section of XCO-MTB racing, suggested the following:

> "…competitive cross-country cyclists should focus on fitness aspects that will allow to recover quicker and develop technical aspects of bike handling…enabling greater efficiency during downhill riding…"

Appropriately, it very well could be the case that riders can recover quicker by increasing their bike handling ability, or at the very least, improving bike handling on descents could improve overall performance. To date however, bike handling remains multivariate, immeasurable and difficult to understand; herein lies the issue.

Chapter 3

AIMS & STRUCTURE

3.1 Background

Olympic format cross-country mountain bike racing features an equal amount of elevation gain and loss, though measures of cycling economy are significantly reduced on descents. The ability to navigate these sections more quickly without the addition of propulsive work could reduce overall oxygen uptake, however the quantification of non-propulsive cycling performance is currently inhibited by lack of technology available. With current tools, scientists are able to accurately assess mechanical propulsive work, but there is nothing commercially available to assess the economy by which a cyclist can navigate the bicycle.

3.2 Aims

Given the background of work done in research surrounding XCO-MTB, there are clear pathways to new discoveries. Thus, the aims of this thesis were to:

1) compare the physiological demand of descending on-road versus off-road, and to determine the effects on performance of the elimination of propulsive work during off-road descending;
2) design and validate a device to measure brake power in bicycle disc brakes;
3) quantify data recorded on a brake power meter during simulated cross-country mountain bike racing to understand the effects of braking on performance;
4) compare braking work done between experienced and inexperienced mountain bikers;
5) determine a method that can account for brake work done when the rear wheel is skidding;
6) validate an algorithm that reduces brake data to a single-number metric that can explain variation in descending performance.

3.3 Thesis structure

To address the aims of this thesis, six experimental investigations were devised and conducted. These are written and presented as manuscripts suitable for stand-alone publication in refereed academic journals. Individually, these manuscripts can stand alone, and are either published (in which case the publication is shown in the Appendices) or in review. These are written and presented as such because it makes the dissemination of the information much more practical and reduces the need for much more extraneous formatting and repetition. It is important to note that the direction of these individual manuscripts evolved throughout this thesis where new questions arose. Moreover, the hypotheses in each manuscript were derived from one preceding it, making this stand-alone research sequence follow a communicable story suitable for a doctoral thesis. Often times, these manuscripts were edited to suit specific Journal style (e.g. 'Discussion & Implications' for *Sports Biomechanics* versus 'Discussion' for *European Journal of Sports Science*). Below are individual, general abstracts for each experimental study.

Study 1 (Chapter 4): Eight nationally competitive cross-country mountain bike racers completed a ramp-style laboratory test to exhaustion on a cycle ergometer. Through respiratory gas analysis, the power output at the respiratory compensation point was determined. Participants then undertook three experimental trial on a closed mountain bike track which incorporated an ascent completed at power output associated with the respiratory compensation point leading in to a descent that was completed at race pace. All participants rode the same bike that was outfitted with six accelerometers, and also wore a portable metabolic gas analyser and heart rate monitor. In a random order, participants firstly descended an off-road track twice; in one instance they were allowed to pedal while they were instructed to coast in the second instance. During the last trial, they descended a forest road that ran parallel to the mountain bike descent, and were instructed to maintain the average velocity of the preceding two trials. Vibration exposure was significantly higher on the mountain bike descent when compared with the road descent, which led to significantly elevated heart rate and oxygen uptake. While vibration exposure was not different between the mountain bike descending pacing strategies, the coasting trial had significantly reduced oxygen uptake, and importantly, did not negatively affect performance. Thus, it was determined that a purposeful reduction in propulsive work during descents could positively benefit recovery during mountain bike competitions without impacting performance. It was henceforth determined that future investigations should seek to understand the efficiency of navigating the bicycle, which could have to do with the way the brakes are used.

Study 2 (Chapter 5): A bicycle brake power meter was constructed to measure the work done through the use of the brakes during cycling. One experienced mountain biker completed 408 braking trials on a flat, tar-sealed road (n=348) and flat dirt path (n=60) over five days on the bicycle outfitted with this device. Energy lost to drag and rolling resistance was added to the work done through braking in each braking event; this total energy removed from the bicycle-rider system was compared with the change in kinetic energy of the bicycle-rider system. Analysis highlighted that the change in kinetic energy was not different from the total energy removed from the bicycle-rider system. Similarly, there was a strong linear relationship with these two values. It was therefore determined that this bicycle brake power meter was a valid means of assessing the energy removed during braking while cycling, and it was recommended that future research should quantify braking during simulated racing.

Study 3 (Chapter 6): Ten nationally competitive mountain bike racers undertook a three-lap simulated cross-country mountain bike time trial using the same mountain bike outfitted with the brake power meter and a propulsive power meter. Despite propulsive work significantly reducing following the first lap, performance time in each lap did not change. Brake power meter data intimated that the maintenance of lap time was due to reductions in brake work and the time spent braking following the first lap. It was surmised that braking efficiency increases after repeating a track at race pace, which counterbalances performance decrements due to fatigue. Most of the braking on the track used in this study occurred on descending and turning sections, and the determination was made to investigate these sections more closely.

Study 4 (Chapter 7): A total of 18 volunteers participated in a trial that sought to determine difference in braking and performance between experienced (n=8) and inexperienced (n=10) mountain bikers. A 76.5 m track was taped to 1.5 m wide, which went down a hill on a forest road before leading in to a 180º turn on grass. Participants completed three trials each on the track while utilising a mountain bike outfitted with the brake power meter but no chain to prevent propulsive work. The mean of all variables were calculated from the second and third trials of each participant, and the track was virtually segmented by terrain type post-hoc. Brake power had a significant negative association with performance time, which indicated that faster riders were completing brake work over a shorter period of time. Sectional analysis highlighted that experienced riders wait until longer to brake, which increased the time spent moving quickly and ultimately reduced performance time. Moreover, it was discovered that inexperienced riders are heavily reliant on the rear brake, which has a negative impact on overall braking. The findings surmised that inexperienced riders may be able to perform better on descents and turns by learning to use both brakes more evenly and waiting longer to brake.

Study 5 (Chapter 8): It had been noted that skidding occurred during mountain biking, which equated to 0.3% of lap time. The methods utilised to calculate power relied on the angular velocity of each wheel; henceforth any time the wheel was skidding there was no work being recorded which was not reflective of actual brake work being done. This study tested the possibility of utilizing the angular velocity of the front wheel to calculate the rear brake power during braking events with a mixture of skidding and non-skidding. One experienced mountain biker completed 28 braking trial with a mixture of skids and non-skids on a mixture of a flat, tar-sealed road and a flat dirt path. Correcting for rear brake power by utilising front wheel angular velocity proved to be a valid means of calculate the change in kinetic energy during skidding and not skidding. It was concluded that rear brake power calculated with the present correction would reflect actual energy lost during braking.

Study 6 (Chapter 9): The multivariate performance models utilizing brake metric may be difficult to assess for some uses, which could be a barrier to brake power meter utilization. Nine mountain bikers descended mountain bike track three times using a bike outfitted with a brake power meter to determine the efficacy of brake power meter data to describe descending performance with a single metric. Traditional brakes measures were calculated to determine their association with performance; additionally, a normalized brake work algorithm was utilised which calculated brake power as a proportion of kinetic energy. The normalized brake work was significantly associated with performance time (r^2=0.929) and had a stronger association than other measures investigated. This study underscored the validity of the normalized brake work algorithm to describe descending performance based on a single braking metric, which should enhance the value of brake power meter data for training purposes.

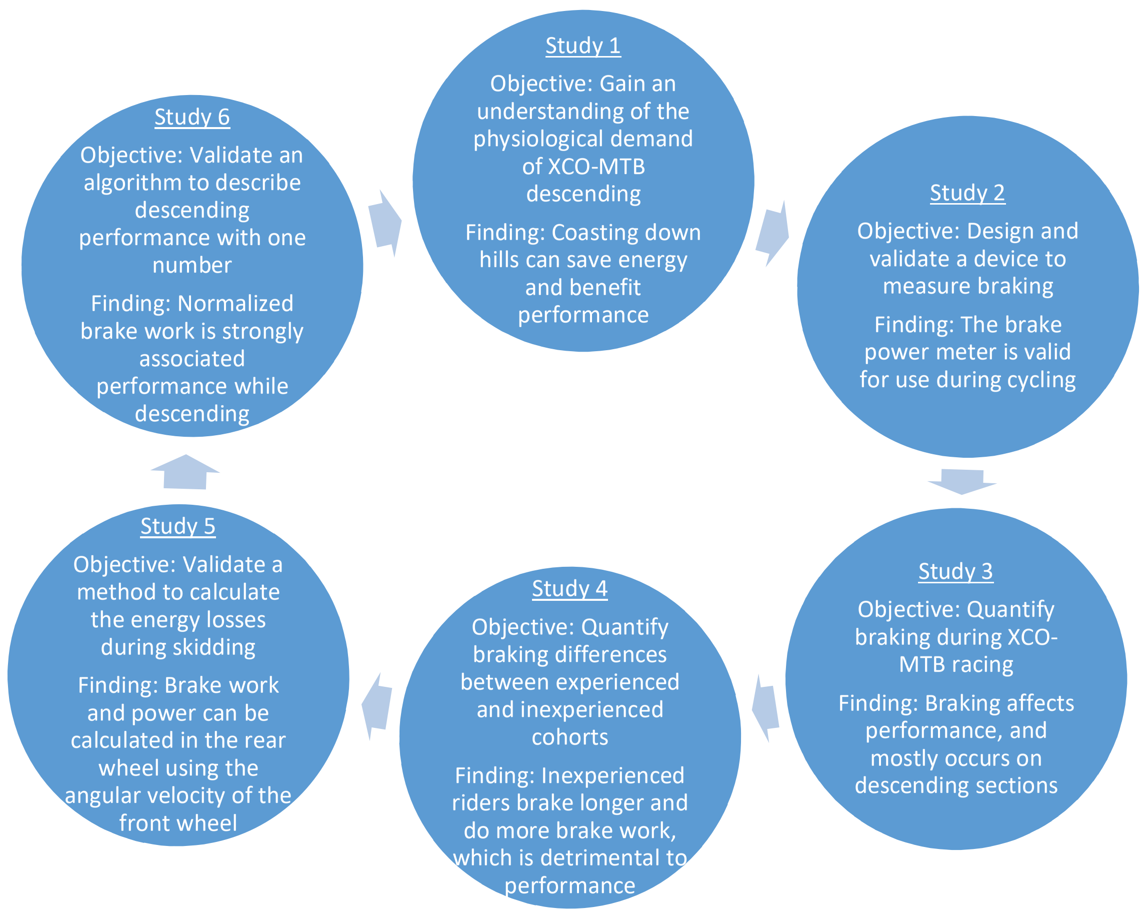

Figure 3.1. Thesis structure schematic.

Chapter 4

PERFORMANCE AND PHYSIOLOGICAL EFFECTS OF DIFFERENT DESCENDING STRATEGIES FOR CROSS-COUNTRY MOUNTAIN BIKING

4.1 Abstract

This study investigated the performance-related feasibility and physiological benefits of purposefully eliminating propulsive work while descending in mountain biking and compared values to those measured during road descending. Participants cycled uphill on a road at race pace before descending over three conditions (off-road pedalling; off-road coasting; road coasting). Relatively low power output during off-road pedalling was associated with a greater oxygen uptake ($p<0.001$) when compared with off-road coasting despite no difference in vibration exposure ($p>0.05$). Importantly, pedalling did not invoke a performance benefit ($p>0.05$) on the descent used in this study. Significantly greater heart rate and oxygen uptake (both $p<0.0001$) were observed between road and off-road descending, likely caused by the increase in terrain-induced vibrations ($p<0.0001$) experienced between the bicycle and rider. Results indicate that reducing propulsive work during descending can improve recovery without being disadvantageous to performance. Similarly, the vibrations experienced during road descending are

relatively low, and further reduce oxygen cost. In an effort to increase efficiency, it is recommended that mountain bike athletes focus on skills to increase descending speed without the addition of pedalling, and that equipment be used to decrease vibrations nearer to those seen on the road.

4.2 Introduction

Olympic format cross-country mountain bike racing (XCO-MTB) takes place over varying terrains, with high-intensity high-power ascending sections separated by relatively lower intensity descents. Despite a pattern of highly intermittent mechanical propulsive work (Macdermid & Stannard, 2012), measured physiological variables remain elevated (Impellizzeri *et al*. 2002; Stapelfeldt *et al*. 2004), even on the descents, as athletes contend with technical terrain and obstacles (Gregory *et al*. 2007). During sections where propulsive work requirement is low, such as on the descents, recovery is inhibited due to non-propulsive work from the musculo-tendonous damping of vibrations (Macdermid *et al*. 2014) as well as steering and postural work of the upper body (Hurst *et al.* 2012). The lack of change in physiological variables on the downhill sections are in contrast to road cycling where riders are seemingly afforded better recovery in competition (Lucia *et al*.1999; Padilla *et al*. 2000) which is likely due to reduced vibration exposure because of the smoother riding surface (Macdermid *et al*. 2015). Technological systems designed to reduce soft impacts and vibrations (Macdermid, *et al*. 2014; Macdermid *et al*. 2017) can potentially reduce non-propulsive work during XCO-MTB (Macdermid *et al.* 2015), but physiological demands remain higher than those on the road. As vibration exposure may be exacerbated with increases in velocity (Macdermid *et al.* 2014), descending parts of the course may indicate the greatest magnitude of difference between road and off-road riding, however no attempt has been made to quantify differences in off-road and road descending.

Other attempts to maximize energy efficiency in cycling sports have focused on pacing strategies. Effective road cycling time trial pacing strategies utilize increased power on uphill portions and reduced power on descents (Atkinson & Brunskill, 2000; Atkinson *et al*. 2007) to provide the best performances. These strategies appear to work because competitors stand to gain the least time on faster parts of the course (e.g. descents) and gain the most time on the slowest parts of the course (e.g. ascents). In practice, this strategy enhances recovery while descending to help the athlete exercise at a higher intensity on subsequent ascents. Such a tactic could be recommended to attenuate reduced efficiency and benefit overall performance in XCO-MTB as uphill climbing ability remains most important to race outcome (Abbiss *et al.* 2013; Martin *et al.* 2012). This is corroborated by previous work showing that downhill mountain biking has decreased dependence on propulsive work (Hurst & Atkins, 2006) and increased emphasis on rider skill (Chidley *et al*. 2014; Mastroianni *et al*. 2000). While these findings tend to suggest that propulsive work could be purposefully reduced during XCO-MTB descending to help the next ascent without contributing to an overall performance decrement, scientific investigations have yet to explore this area specifically.

Therefore, this study was conducted to investigate the performance and physiological demand of either pedalling or not pedalling while navigating a XCO-MTB descent under the simulated intensity of a XCO-MTB race. A secondary aim was to compare the off-road strategies to reduce propulsive and non-propulsive work done with a road descent of similar duration and speed. It was hypothesized that off-road coasting would not alter performance but that the reduced propulsive work would lead to a decreased oxygen uptake compared to pedalling. It was also supposed that a reduction in non-propulsive work during the road descent would further reduce oxygen uptake.

4.3 Methods

Participants, Procedures and Equipment

Eight nationally competitive XCO-MTB athletes (mean ± SD: age= 27 ± 7 years, height= 174 ± 8 cm, mass= 70.3 ± 11.6 kg, power at respiratory compensation point (RCP)= 300.1 ± 48.3 W, RCP (percent of maximal oxygen uptake)= 74.9 ± 3.7 %, VO_{2max}= 68.1 ± 9.8 $ml \cdot min^{-1} \cdot kg^{-1}$) volunteered for this study which was approved by the institutional Human Ethics Committee. Testing involved one session in the laboratory and one session on a purpose built track (Kohitere Forest, Levin, NZ) at least 24 hours later. The laboratory session involved a ramp-style test to exhaustion (Lode Excalibur Sport, NL) commencing at 100 W and increasing by 25 W per minute until the participant could no longer maintain the required power output. Throughout this test heart rate (Polar Electro, Kempele, Finland), expired air (K4b2, Cosmed, Italy) and power output (W) were measured. Expired air data averaged every 15 s enabled calculation of VO_{2peak} and RCP to determine exercise intensity for the hill climb component specific to that reported in race conditions (Lucía *et al*. 2000) for the field trial.

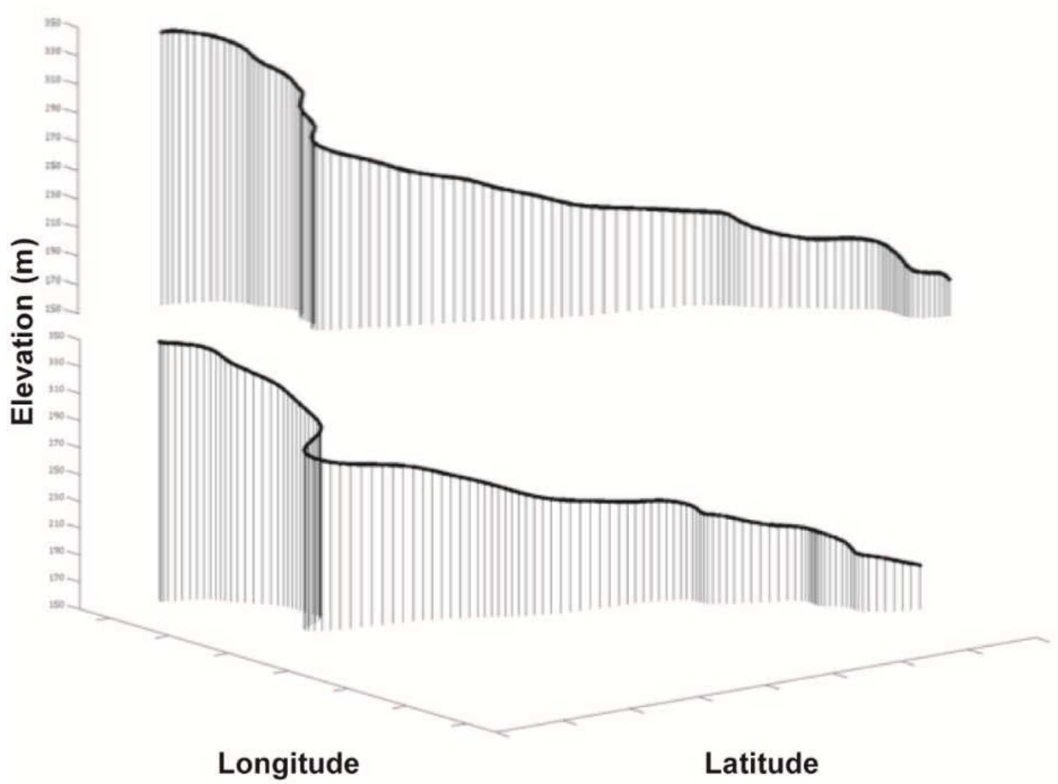

Figure 4.1 Descent profiles with elevation (m) for A. DH_C and DH_P (1.01 km, -16.3% gradient), and B. DH_R (1.03 km, -15.7%).

Off-road descents with coasting (DH_C) or pedalling (DH_P) and road descent (DH_R).

Participants used the same bike (Anthem 27.5 2, Giant Bicycles, NZ) set at personal preferences for the field trials. All participants were familiar with the track used (1.0 km, -16.3% gradient; Figure 4.1). Following an individualized race-specific warm-up for 15 minutes, participants completed a coasting familiarization trial. Each subsequent test trial began with an ascent at RCP to ensure descents were completed under racing stress. Participants completed in a randomized order the same descent at race pace while either pedalling (DH_P) or coasting (DH_C). The participants then completed a parallel descent on a forest road of comparable characteristics (DH_R; 1.0 km, -15.7% gradient; Figure 1) at the mean velocity of DH_P and DH_C.

Data Recording

Power output (SRAM Quarq S2275, USA) (**Appendix I**) and heart rate (Garmin Edge 510, USA) were continuously sampled and logged every second throughout the field trial, while VO_2 ($ml \cdot min^{-1} \cdot kg^{-1}$) was measured breath by breath on the Cosmed K4b2 and reduced to 15 s averages. Data recorded from the power meter and GPS device were transmitted to a conventional personal computer and processed with the Garmin Training Centre software (version 3.6.5).

Wireless, tri-axial, gyroscopic accelerometers (Emerald, APDM, OR, USA) sampled at 128 Hz were used in a synchronised data logging mode to measure accelerations in accordance with methods reported elsewhere in similar studies (Macdermid *et al*., 2015; Macdermid *et al*., 2014, Miller & Macdermid 2015). The accelerometers were placed on the lower left arm (frontal distal position); left lower leg (frontal, distal position); seat post (within 10cm of saddle-rider contact area); lumbar region of lower back; and medial forehead (Macdermid *et al.* 2014). The accelerometers were synchronised with the Garmin Edge 510 and the Cosmed K4b2 enabling specific terrain sections to be marked across all units. Data were analysed using MATLAB R2014b for total (XYZ) accelerations (Macdermid *et al.* 2014).

Statistical Analyses

Descriptive data (mean ± SD) for time (s), power (W), HR, and relative oxygen uptake (VO_2; $ml \cdot min^{-1} \cdot kg^{-1}$) separately for the ascent and descent of each trial and were analysed using one-way repeated-measures analysis of variance (ANOVA). Two-way repeated-measures ANOVA was used to compare total RMS data across each accelerometer for each trial (condition*location) as well as to compare changes in heart rate and oxygen uptake throughout each trial (condition*time). Correlations (Pearson's r) were determined comparing all performance variables. Where significant difference was found the main effect was analysed using Bonferroni post-hoc testing. All statistical analyses were performed using GraphPad Prism 6, significance set at $p<0.05$.

4.4 Results

Uphill variables including total acceleration amplitude ($F_{(2, 84)}$=1.512, p=0.2265), heart rate ($F_{(2, 14)}$=0.9831, p=0.3986), VO_2 ($F_{(2, 14)}$=0.4187, p=0.6659), power output ($F_{(2, 14)}$=1.113, p=0.3559) and time ($F_{(2, 14)}$=0.5568, p=0.5852) were not significantly different between trials, indicating the uphill portion of this study was well controlled and that the participants entered each descending trial in a similar physiological state.

Maximum power during DH_P was 526.4 ±151.0 W, while average power was 18.8 ±11.6 W from 19.9 ±9.8 s of pedalling. The power recordings during DH_P were significantly greater ($F_{(1, 7)}$=20.82, p=0.0026) than DH_C and DH_R, during which participants did not pedal and thus recorded values of 0 W. However, analysis of velocity showed no statistically significant difference (DH_C= 7.3 ±1.4, DH_P= 7.5 ±1.5, DH_R= 7.3 ±1.4 $m \cdot s^{-1}$; $F_{(2,14)}$=0.9014, p=0.4283), and was accompanied by no significant difference in time (Figure 2C) to complete each trial (DH_C=142.5 ±29.2, DH_P=139.9 ±29.2, DH_R=145.1 ±29.3; $F_{(1.135, 7.948)}$=2.615, p=0.1438). Results recorded for VO_2 (Figure 4.2B) were different between all trials ($F_{(1.152, 8.062)}$=131.7, p<0.0001), equalling 31.7 ±3.9, 35.2 ±4.8, and 20.1 ±2.6 $ml \cdot min^{-1} \cdot kg^{-1}$, corresponding with 47.4 ±6.7, 52.5 ±6.7, and 30.1 ±5.2 % of maximal oxygen uptake for DH_C, DH_P and DH_R, respectively. This was accompanied by significantly different heart rate recordings (DH_C= 166.8 ± 7.7, DH_P= 171.8 ± 6.6, DH_R= 132.0 ± 10.4; $F_{(1.519, 10.63)}$= 200.3, p<0.0001; Figure 4.2A) between trials, however post-hoc testing revealed there was no significant difference between DH_P and DH_C ($p>0.05$).

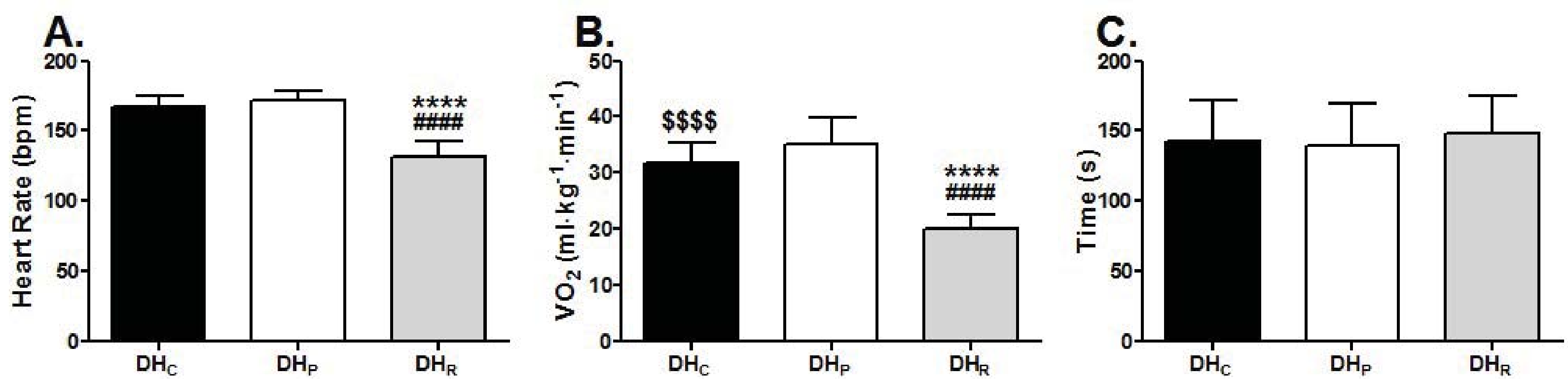

Figure 4.2 Mean ± SD for values of A. Heart Rate (bpm) and B. VO_2 ($ml \cdot min^{-1} \cdot kg^{-1}$) and C. Time (s).

Post-hoc analysis $$$$ (p<0.0001) when compared with DH_P; **** (p<0.0001) when compared with DH_R, #### (p<0.0001) when compared with DH_C.

Off-road descents with coasting (DH_C) or pedalling (DH_P) and road descent (DH_R).

Maximum ($p=0.501$) and average ($p=0.489$) power output were not related to time for DH_P. Time for DH_P was significantly correlated ($r=0.957$; $p<0.001$) with time for DH_C. Values for oxygen uptake were significantly related between DH_P and DH_C ($r=0.971$; $p<0.0001$) and between DH_C and DH_R ($r=0.708$; $p=0.049$) but not between DH_P and DH_R ($p=0.070$). VO_{2max} was related to VO_2 in DH_R ($r=-0.674$; $p=0.047$), but not between any other variables.

Analysis of physiological variables averaged every 15 s (Figure 4.3) indicated a significant main effect for condition ($F_{(2, 184)}=186.4$, $p<0.0001$) and time ($F_{(9, 184)}=25.81$, $p<0.0001$) with a significant interaction between condition*time ($F_{(18, 184)}=5.748$, $p<0.0001$) for VO_2. Analysis of heart rate also revealed significant main effects for condition ($F_{(2, 183)}=272.7$, $p<0.0001$) and time ($F_{(9, 183)}=31.29$, $p<0.0001$) and a significant interaction between condition*time ($F_{(18, 183)}=10.09$, $p<0.0001$). Post hoc testing of $\dot{V}O_2$ and heart rate (Figure 4.3) identified differences ($p<0.05$) at the 45 s time point when comparing DH_R and DH_P, and from the 60 s time point for both DH_C and DH_P compared with DH_R, indicating an increased ability to recover during DH_R.

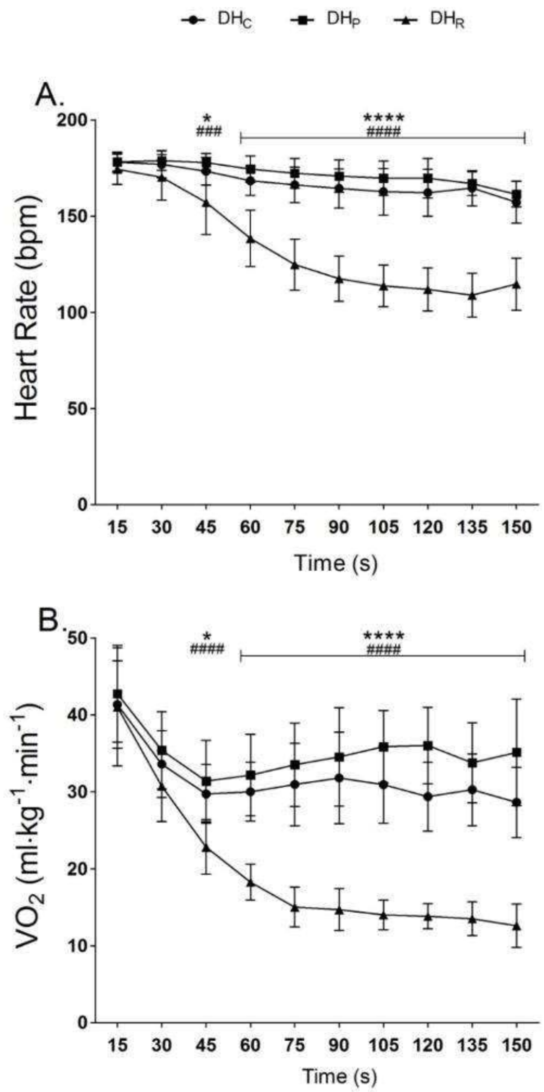

Figure 4.3 Mean ± SD of A. heart rate (bpm) and B. VO_2 (ml·min^{-1}·kg^{-1}) continuously sampled and reduced to 15 s averages.

Post-hoc analysis * ($p<0.05$), **** ($p<0.0001$) significant difference between DH$_C$ and DH$_R$; ### ($p<0.001$), #### ($p<0.0001$) significant difference between DH$_P$ and DH$_R$.

Off-road descents with coasting (DH$_C$) or pedalling (DH$_P$) and road descent (DH$_R$).

Two-way ANOVA of total accelerations (Figure 4.4) revealed a significant main effect of location of accelerometer ($F_{(5, 42)}$=39.44, p<0.0001) and downhill condition ($F_{(2, 84)}$=324.3, p<0.0001) as well as a significant interaction between condition*location ($F_{(10, 84)}$ =22.86, p<0.0001). Post-hoc testing identified accelerations to be significantly lower (p<0.0001) during DH_R at the wrist, ankle, handlebar, and seatpost when compared with DH_P and DH_C, but not significantly different at the lumbar spine or head (p>0.05), indicating increased vibration damping demanded during DH_C and DH_P.

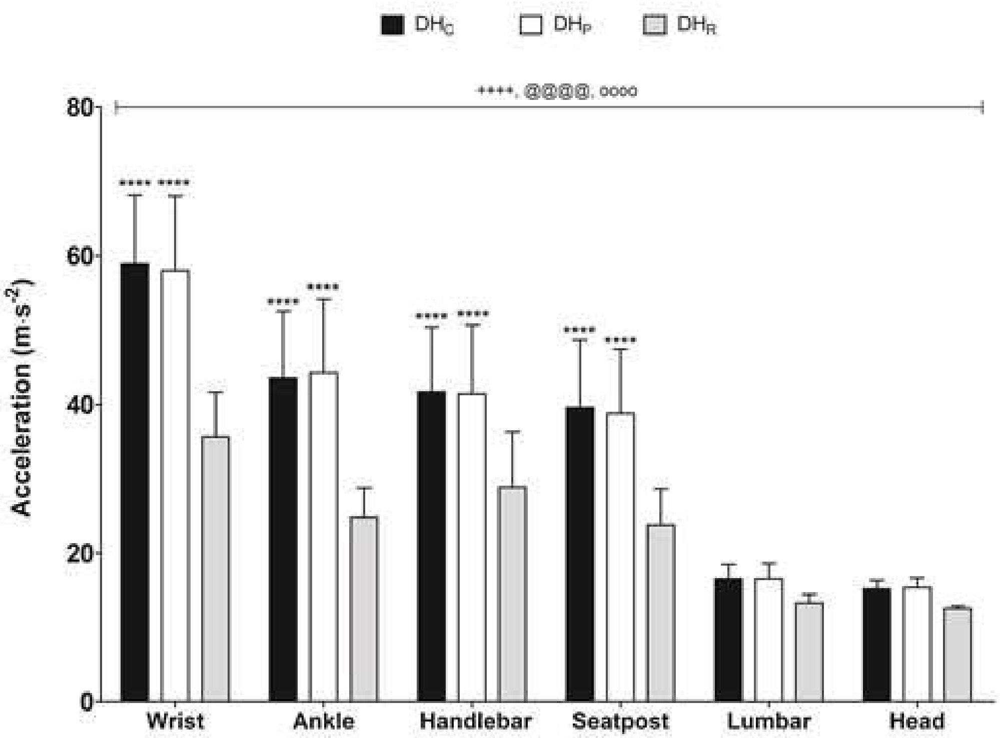

Figure 4.4 Comparison between DH_C, DH_P and DH_R for total accelerations.

++++ ($p<0.0001$) main effect of location; @@@@ ($p<0.0001$) main effect of condition; oooo ($p<0.0001$) interaction between condition*location. Post-hoc analysis **** ($p<0.0001$) when compared with DH_R

Off-road descents with coasting (DH_C) or pedalling (DH_P) and road descent (DH_R).

4.5 Discussion

The primary aim of this study was to investigate the performance and physiological demand of either pedalling or coasting while navigating a XCO-MTB descent at the simulated intensity of a XCO-MTB race. A secondary aim was to compare these demands to an equivalent road descent. The main findings were: a) downhill performance was not changed through the absence of propulsive work; b) oxygen uptake significantly increased with the addition of propulsive work to off-road descending; c) mechanical and soft tissue damping associated with road descents were less than off-road, resulting in significantly decreased oxygen uptake and heart rate.

Uphill variables such as power output, heart rate and VO_2 firstly indicated the demand of the ascent, and also highlighted that riders were stressed similarly during each downhill trial. The key finding is that coasting on the XCO-MTB descent (Figure 4.1) used in this study did not result in a significantly reduced velocity ($DH_C = 7.3 \pm 1.4$, $DH_P = 7.5 \pm 1.5$ $m{\cdot}s^{-1}$) or increased time (Figure 4.2), indicating that this strategy did not negatively impact performance. While oxygen uptake and heart rate were not different at 15 second time points (Figure4. 3) during off-road descents, overall VO_2 was significantly increased when pedalling versus coasting (Figure 4.2). Maximal power during DH_P (526.4 ± 151.0 W) likely exacerbated oxygen uptake, however overall VO_2 increases occurred despite relatively low average power output (18.8 ± 11.6 W) and minimal time spent pedalling (19.9 ± 9.8 s). Importantly, increased VO_2 was not a result of non-propulsive work from vibration damping (Figure 4.4), which may be explained by the similar velocity between trials. While better recovery during intermittent exercise may be important (Tomlin & Wenger, 2001), this study did not investigate how these two strategies affected a subsequent high-intensity ascent which warrants further investigation.

As indicated by the non-significant difference in time (Figure 4.2) when pedalling versus coasting and the non-significant relationship between power output and time when pedalling, these findings agree that downhill performance has less dependence on power output (Hurst & Atkins, 2006) and supports reports suggesting that skill is most important to descending performance (Chidley *et al.* 2014; Mastroianni *et al.* 2000). While skill cannot currently be quantified, its importance is corroborated by the significant relationship between times in DH_P and DH_C, indicating that the fastest riders had the fastest times whether pedalling or not. It is important to point out that despite elimination of mechanical propulsive work (i.e. DH_C), participants in this study displayed a wide range of descending performance (142.5 ±29.2 s). While the importance of ascending prowess for XCO-MTB performance cannot be overlooked, it can be surmised that riders who descend the slowest are disadvantaged before the next ascent regardless of any time they are able to make up by ascending more quickly. Considering the results of this study and the demands of XCO-MTB, athletes can benefit from improvement in specific skills that would allow them to decrease descending time without the addition of pedalling. More research is required to determine these necessary skills.

It was hypothesized that non-propulsive work would be reduced when descending on the road and accompany a decrease in physiological variables. As expected, vibrations were significantly reduced at the wrist, handlebar, ankle and seatpost during DH_R (Figure 4.4). This reduced vibration exposure was associated with significantly lesser (Figure 4.2) oxygen uptake and heart rate in DH_R compared with DH_P and DH_C. After 45 s (Figure 4.3), VO_2 appears to plateau in DH_P and DH_C while values continue to drop throughout the duration of DH_R. Riders who are have a higher level of physical fitness tended to recover to greater extent as seen by the negative correlation between VO_{2max} measured in the laboratory and VO_2 measured during DH_R. We surmise that the reduced vibration exposure eventuated to a decreased musculo-tendonous work requirement (Hurst *et al.* 2012) which would normally absorb the accelerations in order to protect the head and lumbar spine (Macdermid *et al.* 2015; Macdermid *et al.* 2015; Macdermid *et al.* 2014; Miller & Macdermid, 2015a). However, as muscle activity was not directly measured, this explanation remains only speculative. Nevertheless, the data do indicate that reducing vibrations nearer to those seen on the road could further reduce metabolic demand riding off-road and therefore it is recommended that investigations continue to explore equipment (Macdermid *et al.* 2015) designs which can decrease vibration exposure.

Overall, the data support our hypothesis that physiological demand is greater during off-road descending than on-road, and this may help explain differences in what constitutes optimum physiological rider profiles between XCO-MTB and road competitors.

4.6 Conclusion

This is the first study to compare different strategies for approaching descents during XCO-MTB and also to compare off-road and road descending. On the off-road descent used in this study, pedalling was not advantageous and resulted in an exacerbated oxygen uptake. Therefore, it is recommended that athletes focus on skill increases that will allow them to complete descents faster without adding pedalling, which is an area that needs more research. Moreover, physiological responses were significantly greater during off-road descents when compared with the road and can be partly attributed to the terrain demanding greater vibration damping by the body. Future research should continue to investigate equipment that can minimize vibration exposure when riding off-road nearer to values seen on the road to ultimately reduce oxygen uptake.

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STATEMENT OF CONTRIBUTION
TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Matthew C Miller

Name/Title of Principal Supervisor: Prof Stephen R Stannard

Name of Published Research Output and full reference:

Miller, M.C., Macdermid, P.W., Fink, P.W., and Stannard, S.R., Performance and physiological effects of different descending strategies for cross-country mountain biking. European Journal of Sport Science, 17(3): p. 279-285.

In which Chapter is the Published Work: Chapter 4

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate: 90%

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Study design; data collection and analysis; manuscript drafting; manuscript submission

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21/08/2017

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Principal Supervisor's signature

24/08/2017

Date

Chapter 5

VALIDITY OF A DEVICE DESIGNED TO MEASURE BRAKING POWER IN BICYCLE DISC BRAKES

5.1 Abstract

Real-world cycling performance depends not only on exercise capacities, but also on efficiently traversing the bicycle through the terrain. The aim of this study was to determine if it was possible to quantify the braking done by a cyclist in the field. One cyclist performed 408 braking trials (348 on a flat road; 60 on a flat dirt path) over five days on a bicycle fitted with brake torque and angular velocity sensors to measure brake power. Based on Newtonian physics, the sum of brake work, aerodynamic drag, and rolling resistance was compared with the change in kinetic energy in each braking event. Strong linear relationships between the total energy removed from the bicycle-rider system through braking and the change in kinetic energy were observed on the tar-sealed road (r^2=0.989; p<0.0001) and the dirt path (r^2=0.952; p<0.0001). The t-tests revealed no difference between the total energy removed and the change in kinetic energy on the road (p=0.715) or dirt (p=0.128). This study highlights that brake torque and angular velocity sensors are valid for calculating brake power on the disc brakes of a bicycle in field

conditions. Such a device may be useful for investigating cyclists' ability to traverse through various terrains.

5.2 Introduction

Performance in Olympic format cross-country mountain bike racing (XCO-MTB) is characterised by high-intensity pedalling on flat and ascending sections of trail interspersed with lower-intensity efforts on highly-technical or descending sections (Macdermid & Stannard, 2012). The use of on-the-bike power meters has permitted a good understanding of the propulsive work performed during real cycling (Abbiss *et al.* 2013; Impellizzeri *et al.* 2002; Impellizzeri & Marcora, 2007; Macdermid *et al.* 2014; Macdermid & Stannard, 2012; Miller *et al.* 2014; Stapelfeldt *et al.* 2004). By measuring the torque and angular velocity concurrently at some point on the drivetrain (Abbiss *et al.* 2009; Bertucci *et al*. 2005; Gardner *et al.* 2004; **Appendix I**), the information collected from these power meters have been utilised to fine-tune physical training programs for peak athletic performance and currently offer the best method to analyse race and training data (Atkinson *et al.* 2007; Jobson *et al.* 2009; Padilla *et al.* 2000). However, these measurements are strictly propulsive and do little to explain any other interaction the rider has with the terrain or how they utilise necessary skills to efficiently complete a track. Rider skill has been indicated as an important component of XCO-MTB performance (Mastroianni *et al.* 2000), especially during the high-speed and/or technical downhill sections where there is often little propulsive work being done (Hurst & Atkins, 2006). To date, no literature is available describing the quantification of skill, with reports being mostly qualitative (Chidley *et al.* 2014).

A possible way to begin to quantify one aspect related to skill in XCO-MTB could be to measure rider input to the brakes of the bicycle. While often important to maintain a safe speed to negotiate turns or obstacles, any use of the brakes reduces forward velocity and requires subsequent positive—typically propulsive—work to regain or surpass initial velocity. Additional propulsive work increases metabolic energy cost (**Chapter 4**) and could potentially reduce the capacity to perform later on in the course of XCO-MTB competition. However, to this point no literature has been published detailing the measurement of brake usage in cycling.

The most intuitive method for brake measurement would be to measure brake power, which is easily converted to a quantity of energy. Indeed, brake power can be integrated to calculate the work done each time the brakes are used, thus indicating the energy removed from the bicycle-rider system through braking. By estimating aerodynamic drag and rolling resistance, it is possible to account for the majority of resistive forces acting on a cyclist while riding in field conditions (Bertucci *et al.* 2013). Therefore, the sum of aerodynamic drag, rolling resistance and work done in the brakes is indicative of the measurable energy removed from the bicycle-rider system during each braking event. The *law of conservation of energy* states that energy can neither be created nor destroyed; it can only be changed in form. As such, the total energy removed during each braking event is equal to the change in kinetic energy of the bicycle-rider system. By comparing these two energy loss equations, it may be possible to determine the validity of brake power measurements.

Therefore, the aim of this study was to add sensors to measure torque and angular velocity at the disc brakes of a bicycle to determine if it is possible to measure braking power in field conditions on both road and dirt surfaces. It was hypothesised that the total energy removed from the bicycle-rider system would be similar to the change in kinetic energy of the bicycle-rider system on both road and off-road surfaces. The determination was made that a strong linear relationship between the two calculated variables ($r>0.90$) would indicate the validity of brake power measurement.

5.3 Methods

One experienced cyclists (age=30 years; height=1.65 meters; body mass=61.90 kg; 15 years competitive cycling experience) completed 408 brake trials across five different days. Of these trials, four days and 348 braking events were completed on a flat, tar-sealed road, and 60 braking events were completed on a flat dirt path on a separate day. The participant cycled on a mountain bike (Figure 5.1; Trance 1, Giant Bicycles, New Zealand) that was equipped with a device designed by a third party to measure brake power at both the front and rear brakes of the bicycle (Figure 5.1B-C). Hollow aluminium blocks (Figure 5.2A) were fitted to the mountain bike on the standard brake caliper mounting posts. Within these blocks, stainless steel rods (Figure 5.2B) were fixed (Figure 5.2C) perpendicular to the braking surface between an S-Type load cell (Figure 5.2D; PT4000, PT Global, New Zealand) and a separate solid aluminium block (Figure 5.2E) on which the brake caliper (Figure 5.2F; SLX, Shimano, Japan) was attached. The load cells were fixed to the aluminium blocks on the distal end, but allowed to slide proximally where attached to the brake caliper. This configuration allowed the load cell to sense the movement of the brake caliper when the brake lever was squeezed and the pads were in contact with the brake rotor, which was indicative or torque. Brake pads interacted with 203 mm brake rotors (Figure 5.2H; Alligator, Taiwan) which were attached to standard 6-bolt hubs torqued to manufacturer's specifications. A magnetometer (Figure 5.2G) sensed the leading edge of evenly spaced holes in the rotors for the measurement of velocity. Data was collected on a stand-alone battery-powered data logger (Figure 1A; DI-710-UHS, DATAQ Instruments, Akron Ohio, USA) attached to the bicycle's handlebar. The brake power measurements devices and data logger equated to 4.79 kg, which brought the total bicycle mass to 17.28 kg.

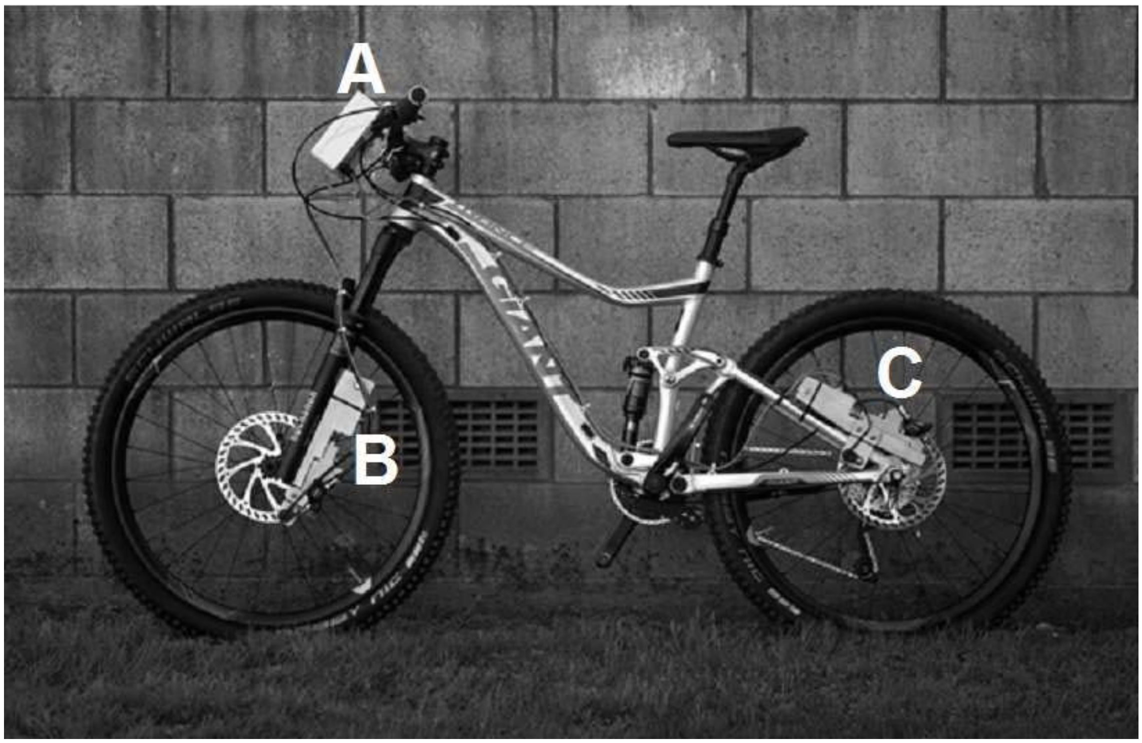

Figure 5.1 Non-drive side view of bike with A: data logger; B: front brake power meter; and C: rear brake power meter.

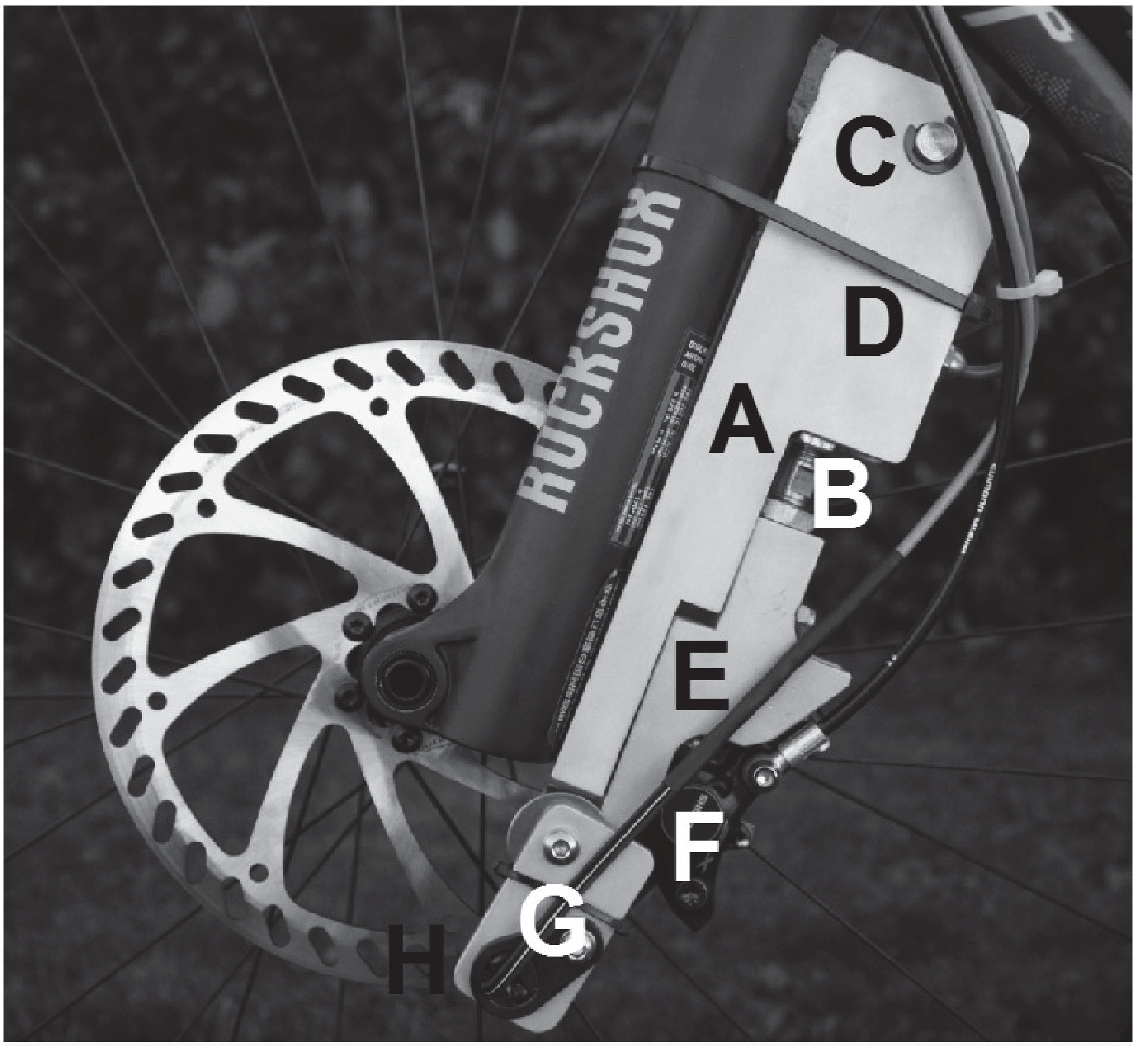

Figure 5.2 Front brake power meter mounted on bicycle fork. A: machined aluminium block mounted to standard bicycle mounting posts; B: stainless steel rod; C: stainless steel fixing pin for load cell; D: load cell housed within aluminium block; E: sliding aluminium block with F: brake caliper mounted; G: magnetometer; H: brake rotor.

Prior to all testing the participant was weighed while wearing cycling gear (1.55 kg), which included cycling clothing, helmet and cycling shoes. The brake calipers were manually centred and rotors torqued to manufacturer's specification by a bicycle mechanic. Tyre pressure was inflated to 0.34 psi per kg of the mass of the rider wearing cycling gear based on standardisation recommendations from (Macdermid *et al.* 2015). Bicycle suspension was mechanically locked out and air pressure was added to the suspension until it did not visually move with the rider seated on the bicycle. The participant was able to accelerate to any speed and decelerate to any speed which allowed a wide range of measurements to be collected. All braking was completed while coasting in a straight line, and there was no instruction on which brake to use or for how long.

The device was calibrated immediately following each trial. To calibrate torque, the bicycle was suspended from the ceiling, which allowed the wheels to spin freely. A 20.0 kg weight was hung from the outer diameter of each tyre at right angles with respect to the ground and axle. Each brake was applied for ten seconds with the weight attached. Using two-point calibration with either the brake applied or not applied, a final 5 s mean voltage signal was converted to a proportional torque given,

$$\tau = F * r \qquad \text{(Eq. 5.1)}$$

where, τ is torque, F is the force due to mass of the 20.0 kg weight and strap times the acceleration of gravity, and r is the distance between the axle centre and weight strap.

Velocity was electronically calibrated using two-point calibration such that 0 V was equal to 0 km/h and 5 V was equal to 16.67 m/s to represent a broad range of cycling velocities (0-60 km/h). Subsequent measures of angular velocity were derived from,

$$\omega = \frac{v}{r} \tag{Eq. 5.2}$$

where, ω is angular velocity, v is equal to either 0 or 16.67 m/s for the two points of calibration, and r is the distance between the axle centre and ground with the rider on the bicycle compressing tyres at the standard pressure.

Data were recorded at 300 Hz and stored in *.wdq format on a micro SD card. Stored files were transferred to a PC and converted to *.xlsx format through WINDAQ Waveform Browser (DATAQ Instruments, Akron Ohio, USA). Excel files were transferred into LabChart version 8.1.5 (ADInstruments Ltd, Colorado Springs Colorado, USA) for calibration. Through separate channels, brake power (Watts) was calculated at each brake by multiplying values of τ and ω at any point when brake torque exceeded zero. Values not exceeding 8 Nm were removed from analysis after visual inspection indicated that these were due to noise from riding surface vibrations. Brake work (joules) was calculated by integrating the power for the combined (front plus rear) brake power. Initial and final velocities were recorded at the initial and final time points of each event.

The *law of conservation of energy* states that energy can neither be created nor destroyed; energy is only changed in form. Therefore, the total energy removed from the bicycle-rider system was compared with the change in kinetic energy of the bicycle-rider system given,

$$\Delta E_K = Brake\ work + E_{rr} + E_d \qquad \text{(Eq. 5.3)}$$

where, ΔE_K is the change in kinetic energy, E_{rr} is energy lost due to rolling resistance, and E_d is energy lost to aerodynamic drag.

For rolling resistance, the predicted energy loss was

$$E_{rr} = mg\mu_{rr}d \qquad \text{(Eq. 5.4)}$$

where, m is the mass of the rider plus bike, g is the gravitational constant, μ_{rr} is the rolling resistance coefficient , and d is the distance travelled. Velocity was integrated to calculate d. For an estimate of the rolling resistance coefficient a value of 0.0218 was used based on Bertucci *et al*. (2013).

Energy lost to aerodynamic drag was calculated as,

$$E_d = \frac{1}{2}c_d A\rho v^2 d \qquad \text{(Eq. 5.5)}$$

where, c_d is the drag coefficient, A is the frontal area, p is air density, v is the average velocity during braking, and d is the distance travelled. Air density was estimated at 1.2250 kg/m^3 based on the air temperature and relative humidity at the time of testing.

The effective frontal area c_dA was estimated using the equation from Bertucci *et al.* (2013). Air speed was assumed to be 0.

$$c_dA = -0.189 + .304h \qquad \text{(Eq. 5.6)}$$

where, h is the rider's height (1.65 m).

The change in kinetic energy was calculated as

$$\Delta E_K = \left[\left(\frac{1}{2}mv_2^2\right) - \left(\frac{1}{2}mv_1^2\right)\right] + \left[\left(\frac{1}{2}\mathrm{I}\omega_2^2\right) - \left(\frac{1}{2}\mathrm{I}\omega_1^2\right)\right] \qquad \text{(Eq. 5.7)}$$

where, m is the combined mass of rider and bike, v is the average velocity throughout the trial, ω is angular velocity, and I is the moment of inertia. I was calculated from

$$\mathrm{I} = mr^2 \qquad \text{(Eq. 5.8)}$$

where, m is the combined mass of the tyre, tube and rim for both wheels and r is the distance between the axle centre and ground when the tyre was compressed at standardised pressure.

Statistical analysis was completed using GrapPad Prism version 5.00 (GraphPad Software, San Diego California, USA) for all 348 trials on the tar-sealed road and separately for the 60 trials on a dirt path. For braking events, descriptive data including mean ± standard deviation (SD) and range (minimum and maximum) were calculated for sample duration (s), initial and final velocities of samples (m/s), mean angular velocity (radians/sec), mean front and rear brake torque (Newton meters), mean front and rear brake power (Watts), brake work (joules), rolling resistance (joules), drag (joules), total energy removed (joules) and the change in kinetic energy (joules) of the bicycle-rider system. For each data set, the coefficient of determination (r^2) was calculated between the total energy removed and the change in kinetic energy of the bicycle-rider system. Linear regression was performed using the total energy removed as the dependent variable, and the change in kinetic energy as the independent variable. Paired student's t-tests were used to analyse the difference between these values. The mean difference between the total energy removed and the change in kinetic energy was reported as a percentage difference with respect to the change in kinetic energy. The p-value was set to $p<0.05$.

5.4 Results

Table 5.1 highlights the mean ± SD, minimum and maximum for measured braking power and its derivatives. Calculated energy losses during braking on each surface are shown in Table 5.2 as negative numbers. For trials completed on the tar-sealed road, the coefficient of determination between the change in kinetic energy and the total energy removed from the bicycle-rider system (Figure 5.3) was $r^2=0.989$ ($p<0.0001$), with a slope of 1.06 and y-intercept of 35.94. A paired t-test revealed no significant difference between the change in kinetic energy and the total energy removed ($p=0.715$), with a mean difference of 0.23 ± 1.24%. Similarly, there was a strong correlation coefficient between values measured for dirt path trials ($r^2=0.952$; slope=1.01, y-intercept=-22.67; $p<0.0001$). Paired t-test results highlighted no difference between the change in kinetic energy and total energy removed during braking trials on the dirt path ($p=0.128$), with a resulting mean difference of 2.46 ± 3.18%.

Table 5.1. Mean ± SD and range for mean power and derivatives during braking.

Surface	Variable	Mean ± SD	Minimum	Maximum
Tar-sealed road	Sample duration (s)	0.9 ± 0.8	0.1	5.7
	Initial velocity (m/s)	5.0 ± 1.3	2.2	10.2
	Final velocity (m/s)	3.3 ± 1.0	0.9	5.8
	Mean angular velocity (rad/s)	11.8 ± 2.8	4.8	21.2
	Mean front torque (Nm)	20.8 ± 5.0	7.0	33.5
	Mean rear torque (Nm)	26.7 ± 8.4	7.8	54.5
	Front brake power (W)	244.2 ± 81.9	0.0	511.0
	Rear brake power (W)	312.4 ± 119.9	0.0	884.0
Dirt path	Sample duration (s)	2.1 ± 0.8	0.7	4.4
	Initial velocity (m/s)	6.4 ±1.5	2.6	10.3
	Final velocity (m/s)	3.1 ± 1.4	0.5	6.8
	Mean angular velocity (rad/s)	13.7 ± 3.7	5.4	21.9
	Mean front torque (Nm)	22.6 ± 7.2	8.1	40.2
	Mean rear torque (Nm)	18.5 ± 7.6	0.0	32.5
	Front brake power (W)	313.0 ± 141.1	103.8	812.1
	Rear brake power (W)	252.8 ± 129.9	0.0	579.0

Note. Values were obtained from 348 braking events on a flat, tar-sealed road and 60 braking events on a flat dirt path. Sample duration was equal to brake time. Initial velocity was the velocity at the onset of braking, while final velocity was the velocity at the end of the braking period.

Table 5.2. Mean ± SD and range for calculated variables of energy loss during braking.

Surface	Variable	Mean ± SD	Minimum	Maximum
Tar-sealed road	Brake work (J)	-490.8 ± 477.5	-76.0	-3671.0
	Rolling resistance (J)	-68.1 ± 74.2	-7.0	-536.7
	Aerodynamic drag (J)	-17.2 ± 31.8	-0.4	-262.0
	Total energy removed (J)	-576.2 ± 574.0	-90.2	-4307.7
	Change in kinetic energy (J)	-577.5 ± 538.6	-75.9	-3733.4
Dirt path	Brake work (J)	-1157.3 ± 631.1	-236.4	-3175.6
	Rolling resistance (J)	-171.8 ± 90.6	-35.0	-486.0
	Aerodynamic drag (J)	-50.9 ± 50.0	-1.5	-231.6
	Total energy removed (J)	-1380.1 ± 758.0	272.9	-3864.8
	Change in kinetic energy (J)	-1346.0 ± 734.0	-225.1	-3601.1

Note. Values were obtained from 348 braking events on a flat, tar-sealed road and 60 braking events on a flat dirt path. The total energy removed from the bicycle rider system was calculated as the sum of brake work, rolling resistance and aerodynamic drag. Paired student's t-tests revealed no significant difference between total energy removed and the change in kinetic energy on either surface ($p=0.715$ and $p=0.128$ for tar-sealed road and dirt path, respectively.

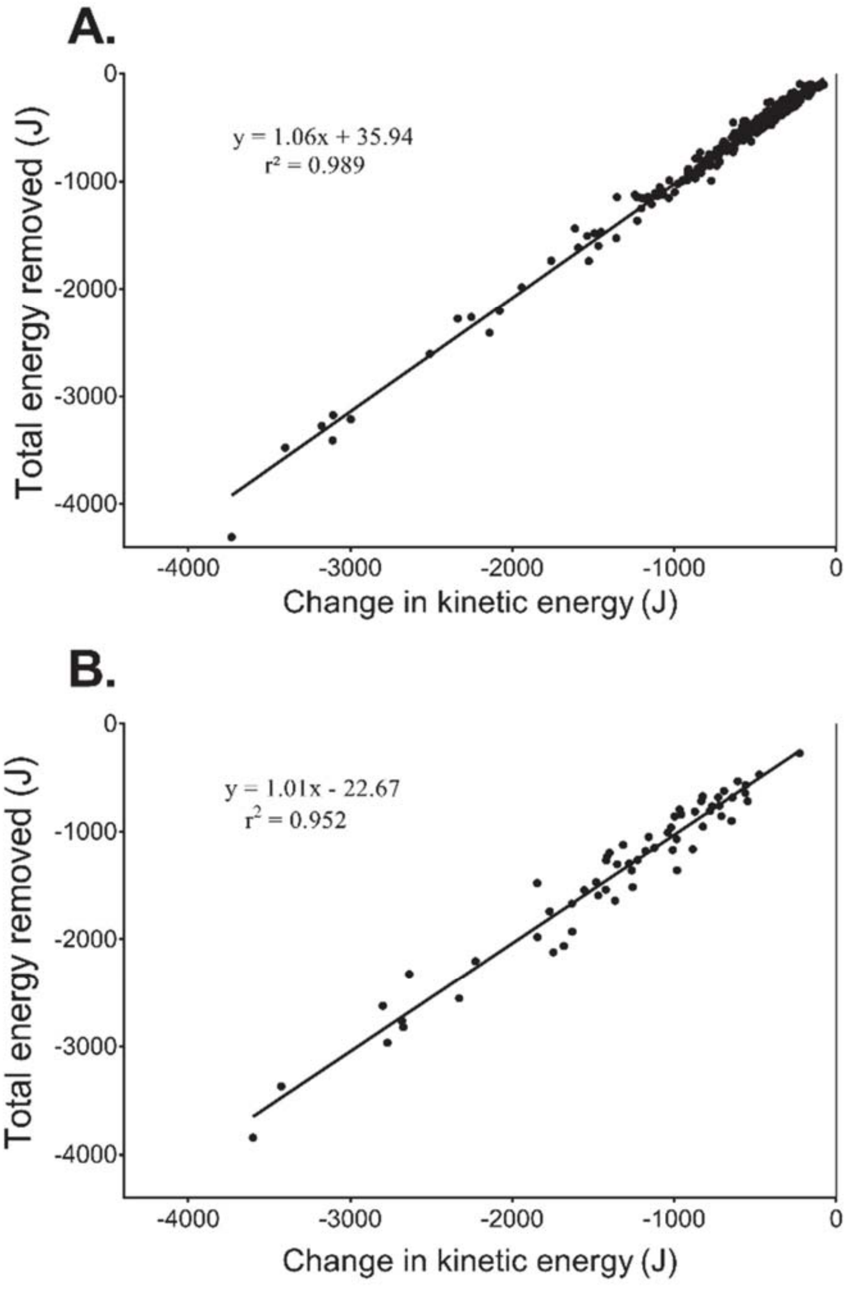

Figure 5.3. Correlation between total energy removed from the bicycle-rider system and the change in kinetic energy for A: 348 braking trials completed on a flat, tar-sealed road; and B: 60 braking trials completed on a flat dirt path.

5.5 Discussion and Implications

The aim of this study was to determine if it is possible to measure braking power in bicycle disc brakes in field conditions. A device was developed to calculate brake power by measuring torque and angular velocity as the brake pads interacted with the brake rotors of each brake on a mountain bike. It was hypothesised that total energy removed from the bicycle-rider system would be equal to the change in kinetic energy of the bicycle-rider system given Equation 5.3. The main findings show that torque and angular velocity sensors on disc brakes of a bicycle are valid means of calculating brake power on road and dirt surfaces.

In this study, the majority of braking events were completed on a flat, tar-sealed road, which was chosen due to the predictability of the riding surface. The flat terrain was chosen because it allowed the calculation of energy losses without needing to account for changes in potential energy due to undulating elevation. While the present study did not account for energy losses outside of estimates of rolling resistance (Equation 5.4) and aerodynamic drag (Equation 5.5) such as sound, work of fracture associated with damage to the tyres or surface, or displacement of the surface in the off road test (among other factors), we were able to explain a large portion of the energy lost while riding the bicycle (Bertucci *et al.* 2013). Estimating these energy losses and adding them to measurements of brake work demonstrated a strong linear relationship (Figure 5.3A) with the change in kinetic energy of the bicycle-rider system during the 348 braking events completed on the tar-sealed road. A similar significant relationship was determined for 60 braking events on the dirt path (Figure 5.3B). These correlations highlighted the goodness of fit for energy calculations on both surfaces, whereby braking events had linearly increasing estimates of energy loss and change in kinetic energy.

The slopes of regression analyses were 1.01 and 1.06 for the dirt path and tar-sealed road, respectively (Figure 5.3A-B), which supported strong linearity of energy loss equations. However, the y-intercepts varied according to the surface ridden, which may be indicative of error from energy loss estimations. The positive sign of the y-intercept on the tar-sealed road (35.94) indicates that the total energy removed is being overestimated, while the negative sign for dirt road trials (y-intercept=-22.67) indicates that the total energy removed is underestimated. These errors may have been introduced through the calculation of rolling resistance (Equation 5.4), which assumes that energy lost does not change with respect to velocity nor account for the different surfaces. Similarly, it is possible that error may have been introduced to the change in kinetic energy (Equation 5.7) given the calculation of the moment of inertia (Equation 5.8), which could not account for the dynamic distribution of the mass of the spokes, rim, tube and tyre.

Despite the potential errors introduced by estimates of rolling resistance and the moment of inertia, the strong linear relationships between energy calculations were corroborated by t-test results that highlighted no difference between total energy and the change in kinetic energy on the tar-sealed road. Therefore, these results indicate the validity of brake work calculations from brake power during 348 on-road braking events. Similarly, t-test results indicated no difference between energy loss calculations on the 60 dirt path braking events. While there was a greater mean of differences between values on the dirt path (2.46%) than on the tar-sealed road (0.23%), this may be attributable to energy lost from additional tire deformation on the uneven surface and movement of the dirt underneath the tyres, though this was not specifically investigated in the present study. Nevertheless, brake power measurement appears robust in the field given these results.

For brake power measurement to be easily adopted in cycling, it is important to display this type of information in a manner that is easily adaptable to other cycling analyses. Figure 5.4 and 5.5 (A-F) demonstrate the readings of torque, angular velocity and brake power in one braking event. In these figures, brake work was done in a relatively short period of time, yet highlights the extent to which even a small braking event can reduce velocity. With brake power readings presented graphically as in Figure 5.4 and 5.5 (E-F), the viewer is shown braking data in a similar manner as readings of propulsive power in cycling analysis software (e.g. TrainingPeaks) and practitioner publications (Allen & Coggan, 2010), which could prove to be useful in future research.

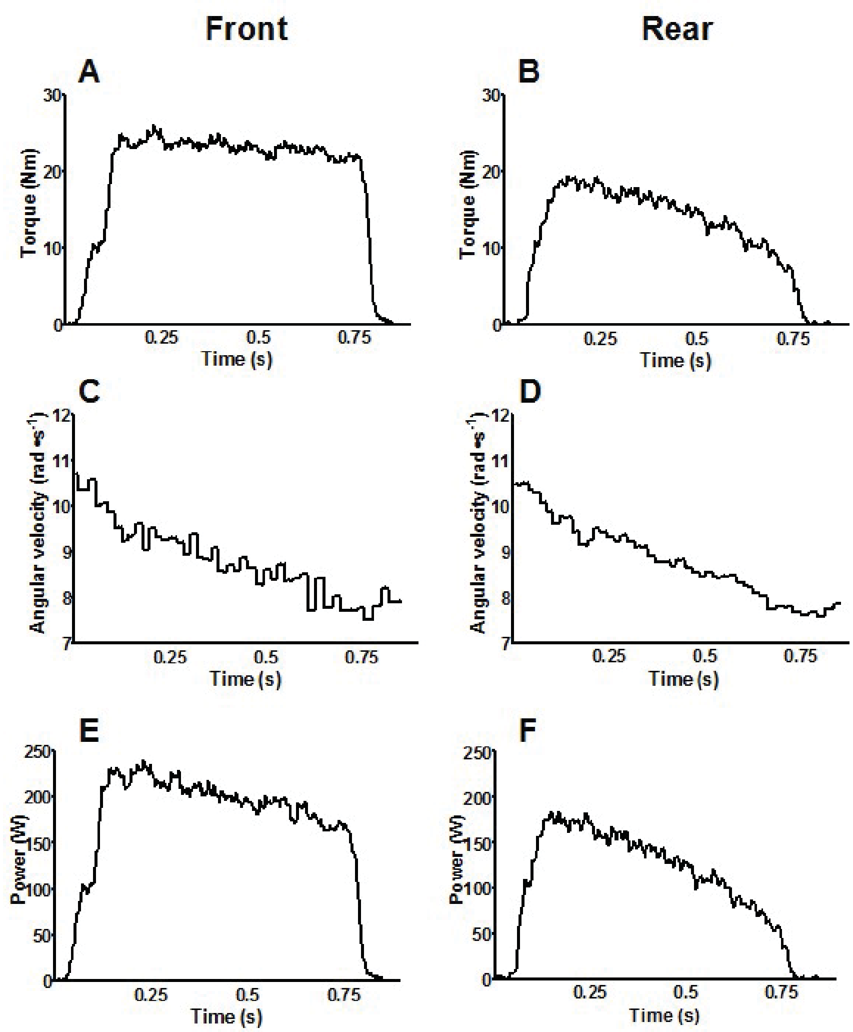

Figure 5.4. Braking example using both front and rear brakes highlighting measurements of brake torque (A-B), angular velocity of the brake rotor (C-D) and resultant brake power (E-F). Initial velocity was 3.7 m/s slowing a combined mass of 79.2 kg (rider plus cycling gear and bicycle) to 2.6 m/s. Sample duration was 0.9 s with a total brake work of 231 J. Mean brake power was 166 and 106 W for the front and rear brakes, respectively.

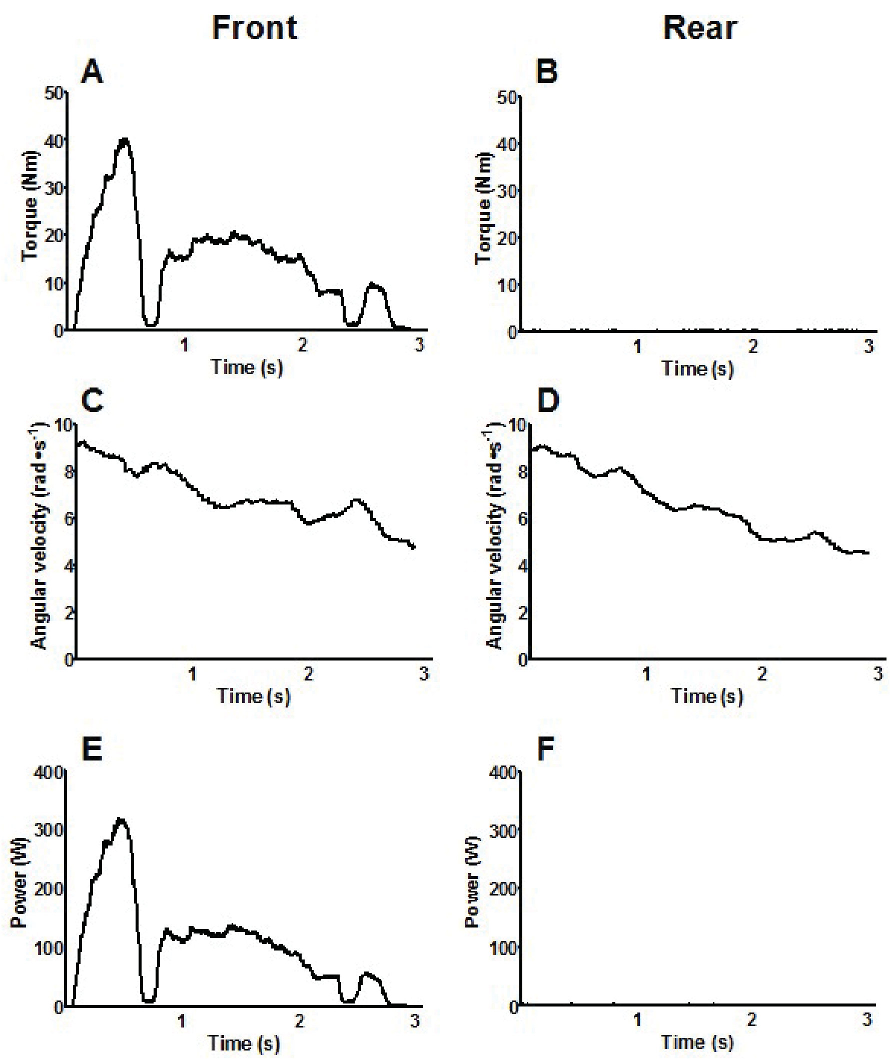

Figure 5.5. Braking example using front brake only. Mean power was 105 and 6 W for the front and rear brakes, respectively. Sample duration was 2.9 s with a total brake work of 322.0 J. Initial velocity was 3.63 m/slowing a 79.2 kg mass to 1.7 m/s with subsequent ΔE_K estimated at 316.8 J.

All braking events in this study were completed between 0.5 and 10.3 m/s (1.8 to 37.1 km/h), which supports brake power measurements within a moderate range of cycling speeds. In the context of racing speeds, the fastest athletes at XCO-MTB races have recorded average speeds of 21.4 km/h (Abbiss *et al.* 2013), though downhill riders travel considerably faster (Hurst *et al.* 2013). The present study did not investigate braking measurements above 37.1 km/h, and despite the strong validity of measurements presented, warrants investigation into the validity of braking variable measurements at higher speeds. A limitation to the present study is the high mass of the devices used to calculate and record brake power, which may affect speed. In building the device, the magnitude of values that would be seen during field riding was not well understood. As such, the device was overbuilt, and increased the total mass of the bicycle to over 17 kg, which is substantially heavier than many racing bicycles. While the current device is therefore not ecologically valid for competitive use, this configuration will allow the quantification of braking data during simulated racing, which remains unexplored.

5.6 Conclusion

This study shows that the addition of torque and angular velocity sensors on the brakes of a bicycle are suitable to measure brake power in field conditions. The quantification of brake work and brake power can help researchers understand how riders use brakes, which may help describe efficiency interactions during XCO-MTB and other forms of cycling. These measurements can lead to novel findings in cycling beyond variables of propulsive mechanical work, and may help describe skill. Just as early descriptive studies proved to be useful to gain good understanding of propulsive cycling performance, it is suggested that a combination of propulsive and brake power meters be utilised in simulated racing conditions for descriptive research of XCO-MTB and other forms of cycling. Thereafter, it is important to compare the braking characteristics of high and low performers, and determine if brake training interventions can positively affect performance.

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STATEMENT OF CONTRIBUTION
TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Matthew C Miller

Name/Title of Principal Supervisor: Prof Stephen R Stannard

Name of Published Research Output and full reference:

Miller, M. C., Fink, P. W., Macdermid, P. W., Perry, B. G., & Stannard, S. R. (2017). Validity of a device designed to measure braking power in bicycle disc brakes. Sports Biomechanics, 1-11.

In which Chapter is the Published Work: Chapter 5

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate: 90%

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Conceptualisation; data collection and analysis; manuscript drafting and submission

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Candidate's Signature

21/08/2017
Date

Stephen Stannard Digitally signed by Stephen Stannard Date: 2017.08.23 20:06:25 +12'00'
Principal Supervisor's signature

24/08/2017
Date

Chapter 6

QUANTIFICATION OF BRAKE DATA ACQUIRED WITH A BRAKE POWER METER DURING SIMULATED CROSS-COUNTRY MOUNTAIN BIKING

6.1 Abstract

There is currently a dearth of information describing cycling performance outside of propulsive and physiological variables. The aim of the present study was to utilise a brake power meter to quantify braking variables during a multi-lap cross-country mountain bike time trial and to determine how brake usage affects performance. A significant negative association was determined between lap time and brake power (800.8 ±216.4 W, $r=-0.446$; $p<0.05$), while the total time spent braking (28.0 ±6.4 s) was positively associated with lap time ($r=0.477$; $p<0.05$). Despite propulsive power significantly decreasing after the first lap ($p<0.01$), lap time remained unchanged ($p=0.25$) which was attributed to both decreased brake work ($p<0.01$) and brake time ($p=0.02$) in both the front and rear brakes by the final lap. A multiple regression model incorporating brake work, brake time and

relative propulsive power was able to explain more of the variance in lap time (r^2=0.935) than when utilising relative propulsive power alone (r^2=0.826). The present study highlights that riders braking contributes to mountain bike performance. As riders repeat a cross-country mountain bike track, they are able to change braking, which in turn can counterbalance fatigue. Further research is required to understand braking better.

6.2 Introduction

Initial descriptive studies of Olympic format cross-country mountain bike racing (XCO-MTB) relied on heart rate data (Impellizzeri *et al*. 2002; Impellizzeri & Marcora, 2007); however, the data were not resolute enough to understand the highly variable propulsive demands of the undulating terrain. Later, as technology advanced, researchers were able to utilise on-the-bike propulsive power meters alongside GPS systems to gain a better understanding of the undulating terrain and variable physiological demands of XCO-MTB racing (Macdermid & Stannard, 2012). It soon became well understood that relative rates of propulsive power were positively associated with XCO-MTB performance (Gregory *et al*. 2007), which has led to the ubiquity of propulsive power meters for the collection and monitoring of racing and training data. Henceforth, data have been used to fine-tune training regimes to help athletes achieve better performances (Jobson *et al.* 2009).

Unfortunately, the data collected from these power meters are strictly propulsive, and cannot explain all of the variation in performance given the technical demands of XCO-MTB. Recent evidence has indicated that variables in addition to propulsive power output can do a much better job at predicting XCO-MTB performance than propulsive variables alone; for example, regression models incorporating an XCO-MTB-specific decision making task and propulsive physiological performance ability have successfully been used for mountain bike performance prediction (Novak *et al.* 2017). Along these lines, a recent XCO-MTB study suggested that braking is an area to investigate (**Chapter 4**) which was apparent after investigating pacing strategies on XCO-MTB descents. Of course, the latter is sensible; while braking in XCO-MTB is often necessary to maintain a safe speed for the negotiation of obstacles or navigation of turns, any braking in excess of that required to control the bicycle would require additional propulsive work to regain speed. Strategies to simultaneously increase speed and also recovery have been encouraged for XCO-MTB competitors due to the increased non-propulsive energy demand (Macdermid et al. 2016), however excess braking could exacerbate glycogen depletion and reduce recovery following high-intensity pedalling efforts (**Chapter 4**). It is clear that XCO-MTB racers adopt some sort of inherent pacing strategy to cope with the demands of the sport, which is evident in the small variation of lap time (Abbiss *et al*. 2013; Martin *et al*., 2012) despite maximal starting efforts (Macdermid & Morton, 2011; Viana *et al*. 2013; Viana *et al*. 2016); however, the premise of this is not understood and could be related to braking. Given the nature of XCO-MTB competition, some description of braking is required to understand how it contributes to racing performance.

By using a device that can measure brake power (**Chapter 5**), it is possible to calculate the same variables at the brakes that are useful and well-accepted for describing propulsive work in cycling (Allen & Coggan, 2012). For example, the energy removed from the bicycle-rider system through braking (i.e. brake work) is analogous to the total energy output for propulsion (i.e. propulsive work), though each understandably has the opposite effect on speed. For the calculation of propulsive power, a time variable is required; one such example may be the time taken to complete a section of interest, in which case the propulsive work done is divided by the duration of this section. The resulting average propulsive power is one metric that has become widely accepted in cycling, and supports the investigation of brake power. By reporting relative rates of propulsive power (W/kg), the effects of gravity are normalised (Gregory *et al*. 2007); as such, it is possible that relative rates of brake work and brake power may be similarly important. Overall, the lessons learned over the years of studying propulsive power data from XCO-MTB may be highly applicable to the brakes and requires investigation.

Therefore, this study set out to quantify braking data using a brake power meter during a multi-lap XCO-MTB simulated time trial, and to determine the relationship between braking and XCO-MTB performance. Based on important and accepted propulsive variables, braking variables such as brake work, brake time and resultant brake power were calculated for each lap and each brake. It was hypothesised that performance, defined by lap time, would be significantly associated with relative rates of propulsive work and also the rate of work done through braking. This study also set out to understand the change in performance by analysing braking and propulsive variables across laps. It was hypothesised that riders would reduce propulsive power across laps following an initial high intensity, but also reduce the amount of brake work done as they became more accustomed to riding the lap at race pace.

6.3 Methods

Participants and procedures

Ten nationally competitive mountain bikers (mean ± SD; age: 29.9 ±8.0; body mass: 72.9 ±12.7 kg; mass of rider plus cycling gear and bike: 90.4 ±12.6 kg; VO_{2max}: 69.4 ±7.1 ml/kg/min) volunteered as participants of this study, which was approved by the University's Human Ethics Committee. All participants used the same bike (Trance 1; Giant Bicycles, New Zealand) with standardized tyre pressure (Macdermid *et al.* 2014) and suspension adjusted to manufacturer's guidelines. The bike was equipped with a crank-based propulsive power meter (S2275; Quarq, Spearfish SD, USA) (**Appendix I**) and also proprietary sensors configured to calculate brake power (**Chapter 5**). Propulsive power (W) was continuously sampled based on manufacturer settings and logged onto a portable recording device at 1 Hz (510; Garmin Ltd., Schaffhausen, Switzerland). Brake torque and angular velocity of the brake rotor were sampled at 128 Hz on the recently validated brake power meter and logged onto a stand-alone data logger (DATAQ UHS710; DATAQ Instruments, Akron Ohio, USA). All equipment was manually zeroed or calibrated immediately before each testing session according to previously used guidelines (**Chapter 5**; **Appendix I & II**).

A purpose-built track (Figure 6.1; 1,240 m, 45 m elevation gain/loss) had not been previously open to riders was utilised for field testing. All participants were first given two laps on the track at a self-selected pace to serve as both a warm up and familiarisation of the track/equipment used. After a 5 minute rest period, participants completed three successive laps of the track at race pace. To delineate the start and end of each lap for data recording purposes, participants pushed the 'LAP' button on the Garmin 510 at the Start/Finish area at the end of each lap.

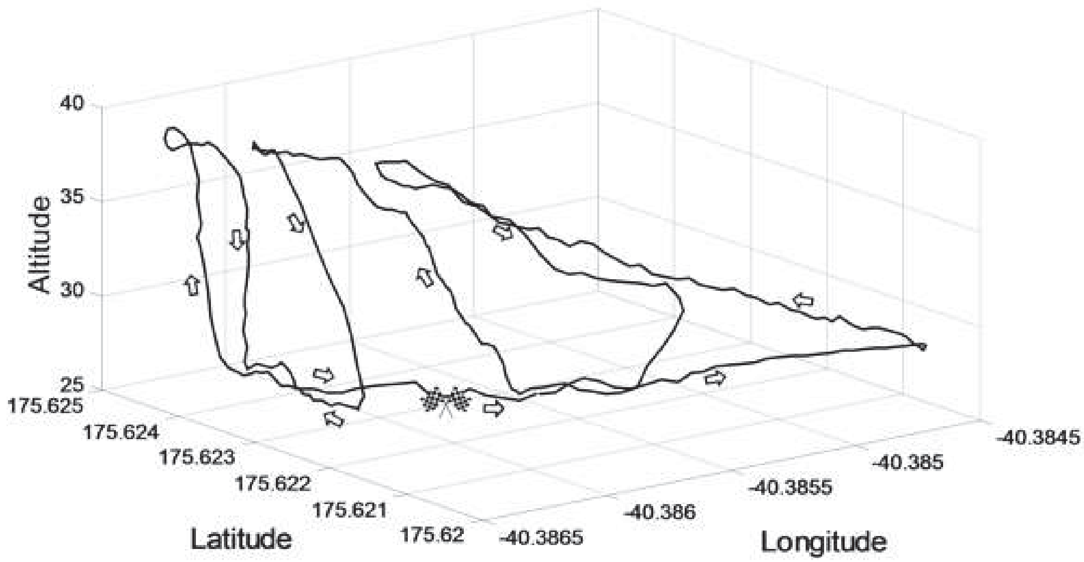

Figure 6.1. Lap profile for XCO-MTB time trial. The track was 1,240 m long and had 45 m elevation gain per lap.

Propulsive power data were tranferred from the Garmin headunit onto a PC using conventional software (Garmin Training Center, Garmin Ltd., Schaffhausen, Switzerland). Measurements of brake torque and wheel velocity were tranferred from the data logger onto a PC using proprietary software (WINDAQ; DATAQ Instruments, Akron Ohio, USA), then transferred to LabChart version 8.1.5 (ADInstruments Ltd, Colorado Springs Colorado, USA) for calibration.

All braking data recorded on the data logger were synced with the Garmin device using MatLab R2011b software (The MathWorks, Inc., Natick, MA, USA) and broken down for analysis. Initial inspection of braking data revealed many low-torque readings while riding, possibly from noise due to surface vibrations translated through the load cells; accordingly, readings below 8 Nm were ignored for analysis. The threshold of 8 Nm was chosen based on an analysis of non-braking periods during the XCO-MTB lap. During a non-braking interval, the largest value of the noise—defined as any value that was present for two or fewer samples—was 6.18 Nm. During a typical braking period, torques averaged around 40 Nm. The 8 Nm threshold was selected as being large enough to eliminate the noise while being small enough to preserve the actual braking periods.

The work (J) done through the use of the brakes was calculated by integrating the product of brake torque and angular velocity for each wheel (front brake work for the front, rear brake work for the rear) and for the two wheels summed together (brake work). The latter was also taken relative to the total mass of the rider plus the gear and bike (relative brake work; J/kg). Brake time was calculated as the total time (s) per lap that both brakes or either brake (front brake time and rear brake time for front and rear brakes, respectively) met or exceeded 8 N m. Brake power was a product of brake work divided by brake time measured in each lap, and further separated into front and rear brakes. Maximum brake power was calculated as the highest power (W) recorded in each lap at any one time using one or both brakes, and was also calculated for front and rear brakes, respectively.

Statistical analyses

All statistical analyses were completed using GraphPad Prism 7 (GraphPad Software, San Diego California, USA). Mean ± standard deviation (SD) for all variables were calculated for each lap of each particpant. The correlation coefficients was calculated between lap time and recorded braking variables for all laps (i.e. ten particicpants who completed three laps each). One-way reapeated measures analysis of variance (ANOVA) was completed for lap time and propulsive power to compare between-lap (i.e. lap 1-3) differences. Brake work, brake time and brake power were analysed separately using two-way repeated measures ANOVA, with the aim of identifying the interaction of independent variables of brake (i.e. front and rear, respectively) and lap (i.e. laps 1-3); henceforth, results indicated the change of the dependent variables with respect to successive laps and also the brake utilised. Where a main effect was observed, Bonferroni's post-hoc testing was used.

A linear regression model was created to determine whether a combination of brake work, brake time and relative propulsive power could be utilised to explain the variance in lap time. Brake work and brake time were integrated into the model based on the results of two-way analysis. To determine the estimation error in the multiple regression model, mean square error (MSE) was calculated as the residual sum of squares divided by the degrees of freedom; estimation error (Error) was calculated as the square root of MSE.

To determine significance, the alpha value was set at 0.05, which is common for use in testing with human participants. By using $p<0.05$, practitioners can apply statistically significant observations in the present study to determine how these benefit the small performance gains desired in individual athletic performance. Actual p values have been reported for ANOVA results.

6.4 Results

Descriptive propulsive and braking variables for each lap (mean ± SD) are presented in Table 6.1. The quantity of total brake work was 24.9% of the total quantity of propulsive work per lap; accordingly, brake time equated to only 8.9% of lap time. Nevertheless, brake time, front brake time and rear brake time, respectively, were significantly related to lap time (Table 6.1). Similarly, braking variables of brake power, relative brake power, front brake power and front brake max power were all significantly related to lap time (Table 6.1).

Table 6.1. Descriptive performance data (mean ± SD) per lap of a simulated XCO-MTB time trial.

Performance variable	Mean	SD	*r*
Lap Time (s)	314.3	37.9	
Propulsive Power (W)	275.8	48.1	**-0.844**
Propulsive Power (W/kg)	3.1	0.4	**-0.909**
Propulsive Work (J)	85187.5	8858.9	-0.244
Brake Work (J)	21174.9	1854.3	-0.331
Relative Brake Work (J/kg)	236.9	26.9	-0.016
Front Brake Work (J)	9931.2	1879.0	-0.333
Rear Brake Work (J)	11243.7	2510.8	0.005
Brake Time (s)	28.0	6.4	**0.477**
Front Brake Time (s)	22.4	5.4	**0.433**
Rear Brake Time (s)	25.0	5.6	**0.536**
Brake Power (W)	800.8	216.4	**-0.446**
Relative Brake Power (W/kg)	8.8	1.6	**-0.566**
Front Brake Power (W)	462.8	112.0	**-0.680**
Rear Brake Power (W)	476.7	171.1	-0.259
Maximum Brake Power (W)	2771.7	1174.9	-0.226
Maximum Front Brake Power (W)	1453.9	337.2	**-0.575**
Maximum Rear Brake Power (W)	1811.4	1212.3	-0.090
Average Brake Power (W)	68.5	11.2	**-0.841**

Note. Data were derived from three sequential XCO-MTB time trial laps completed per participant by 10 participants, for a total of 30 laps. Correlation coefficient (*r*) displayed is that measured between lap time and respective performance variable for all laps. Significant ($p<0.05$) correlation coefficients are highlighted in **bold**.

Two-way ANOVA (Figure 6.2A-C) investigating differences by brake (i.e. front or rear brakes, respectively) and lap (i.e. lap 1-3, respectively) revealed a significant main effect of lap for brake work ($F_{(2,18)}$=6.18; p<0.01), however there was no main effect of brake ($F_{(1,9)}$=1.02; p=0.34) or interaction of brake*lap ($F_{(2,18)}$=0.20; p=0.82). Post-hoc analysis highlighted front and rear brake work were significantly (both p<0.05) reduced in lap 3 when compared with lap 1. Similar analysis of brake time showed significant main effects for lap ($F_{(2,18)}$=4.65; p=0.02) and brake ($F_{(1,9)}$=8.15; p=0.02), but no interaction between brake*lap ($F_{(2,18)}$=1.42; p=0.27). Post-hoc testing revealed that both front and rear brake time were significantly reduced (both p<0.01) in lap 2 and lap 3 when compared with lap 1. No main effect of lap ($F_{(2,18)}$=1.42; p=0.93) or brake ($F_{(1,9)}$=0.09; p=0.77) nor interaction ($F_{(2,18)}$=1.37; p=0.28) were observed for brake power.

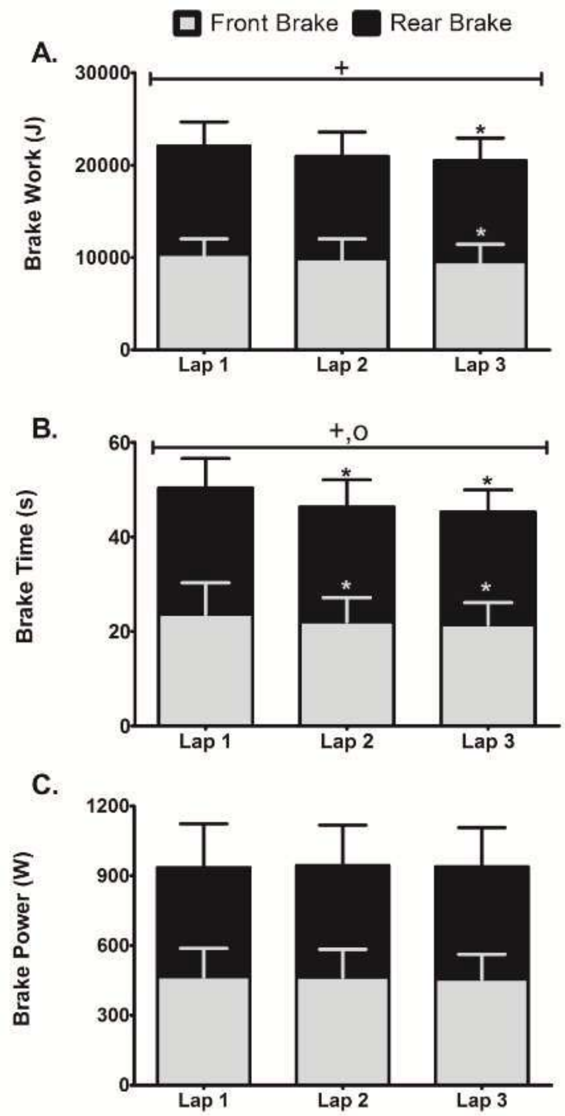

Figure 6.2. A. Brake Work (J), B. Brake Time (s), and C. Brake Power (W) for front (grey) and rear (black) brakes in laps 1-3.

'+' denotes main effect of lap, 'o' denotes main effect of brake
For post-hoc testing '*' denotes significant difference with lap 1.

One-way ANOVA revealed no significant difference for lap time (Figure 6.3A; 308.3 ±36.0, 317.1 ±38.8, and 317.5 ±42.1 s, respectively; $p=0.25$) across three laps despite a significant reduction in relative propulsive power following lap 1 (Figure 6.3B; 3.2 ±0.4, 3.0 ± 0.4, 3.0 ±0.4 W/kg, respectively; $p<0.01$). Based on the overall results from ANOVA, a multiple regression model (Table 6.2) using brake time, brake work and relative propulsive power was generated. This model was able to significantly explain variance in lap time ($r^2=0.935$; $p<0.01$) to within 3.3%.

Table 6.2. Multiple regression model incorporating brake time, brake work and relative propulsive power to explain lap time.

Model	r	r^2	MSE	Error
Lap Time = 540.762 + (1.722 Brake Time) + (-0.002 Brake Work) + (-75.468 Relative Propulsive Power)	0.968	0.935	104.8	10.2

Note. MSE = mean square error, calculated as the residual sum of squares divided by the degrees of freedom; Error = estimation error, calculated as the square root of MSE.

* p<0.05

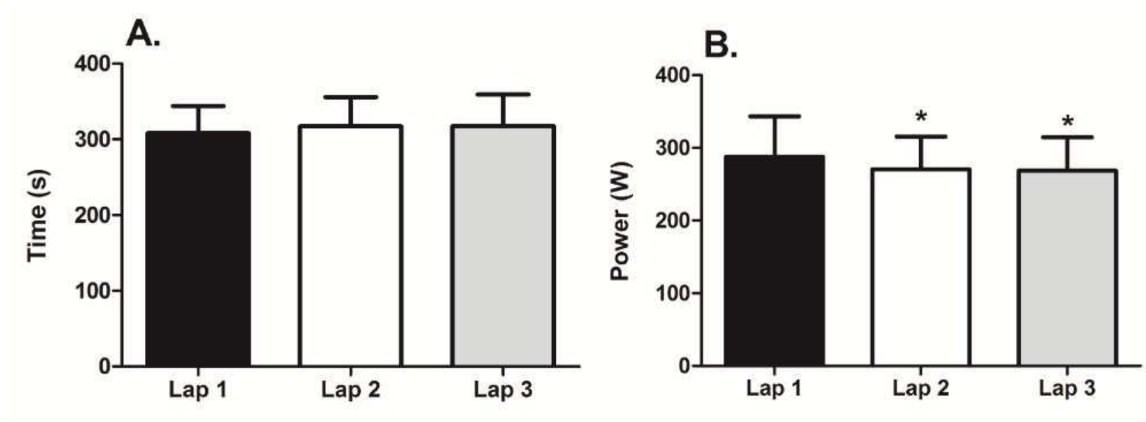

Figure 6.3. A. lap time (s) and B. average propulsive power (W) for laps 1-3.

'*' Denotes significant difference with lap 1.

6.5 Discussion and Implications

This aim of this study was to quantify braking work rates using a brake power meter in mountain biking, and specifically investigated a multi-lap simulated XCO-MTB time trial. It was hypothesised that the fastest riders would not only produce the highest relative propulsive power, but also brake the least. It was also hypothesised that there would be a reduction in propulsive power throughout the time trial, however that this would not be detrimental to performance. The novel findings of this study are that a) brake power and brake time are significantly related to lap time; b) average propulsive power was reduced after lap 1, however there was no significant difference in lap time, attributable to concurrent reductions in brake work and brake time; and c) variations in performance time on the XCO-MTB lap in this study can be explained better when accounting for brake work, brake time and relative propulsive power when compared with relative propulsive power alone.

Absolute and relative propulsive power recorded in each lap were strongly correlated to lap time (Table 6.1), which reinforces the importance of pedalling ability for XCO-MTB race performance (Costa & Fernando, 2008; Gregory *et al.* 2007; Lee *et al*. 2002; Macdermid & Stannard, 2012; Miller & Macdermid, 2015b; Miller *et al.* 2014) . As a mean, brake work equated to 24.9% of propulsive work, and the time spent braking was 8.9% of lap time; nevertheless, strong relationships were observed between braking variables and lap time (Table 6.1). The respective associations of brake power (r=-0.446) and brake time (r=0.477) with lap time indicate that riders are able to navigate the track more quickly when they are braking harder and for less time. Braking in this manner results in a reduction of the time spent travelling at lower speeds when compared with braking at a lower power, ultimately resulting in greater time spent travelling more quickly. Not surprisingly, relative brake power (8.8 W/kg; r=-0.566) had a stronger association with lap time than absolute brake power (800.8 W; r=-0.446); this is understandable given that the kinetic energy of a rider travelling on a bicycle is scaled to mass, and supports previous work done on propulsive power (Gregory *et al.* 2007). Brake power (800.8 W) and maximum brake power (2771.7 W) observed in this study were higher than propulsive recordings of the same values (246 and 1000 W, respectively) (Stapelfeldt *et al*. 2004), which, in comparison, put the nature of braking into perspective. Importantly, the authors noted the strong correlation between lap time and average brake power (r=-0.841; calculated as total brake work during the lap divided by lap time), however this was not analysed further due to it being highly influenced by lap time, and thus, propulsive power; rather, brake power was calculated as a product of brake work and brake time, independent of other variables.

With the exception of front brake work, all measures from the front brake were associated with lap time, which is in contrast to measures recorded in the rear brake (Table 6.1). A possible explanation for this could be the greater standard deviation in rear brake measures, which point to wider differences across individuals. While mean values highlighted in Table 6.1 indicate that measures recorded in the rear brake tended to be greater than those in the front brake, two-way analysis did not show differences in measures of brake work, brake time and brake power between the front and rear brakes (Figure 6.2A-C). These observations challenge traditional understanding of brake usage, whereby a common notion is that the front brake is the most powerful and therefore emphatically utilised; on the other hand, the even braking observed between brakes in the present study may be indicative of the well-trained cohort (Lopes & McCormack, 2010), though this needs confirming. It is important to note that the methods utilised to calculate brake usage require the measurement of the angular velocity of the wheels, and as such any skidding of the wheels produced values of 0 for the respective brake. Inspection of the present data revealed that skidding was non-existent in the front brake; however, skidding with the rear wheel was an average of 1.1 s per lap. As a mean, this was 3.9% of the time spent braking, and therefore this is considered to not affect the present data set. It is clear that any skidding will indeed increase the work done at the rear wheel since a sliding tyre increases the amount of drag when compared with a tyre rolling with the wheel; therefore, more research is required for sufficient quantification of skidding.

Upon further inspection of two-way analysis, it was revealed that riders changed the total magnitude of brake usage across laps. To do this, firstly riders reduced both front and rear brake work by lap 3 when compared with lap 1 (Figure 6.2A). Concomitantly, riders reduced the total amount of brake time in both brakes following lap 1 (Figure 6.2B). Importantly, these observations supported one-way analysis (Figure 6.3A-B) of lap performance: as hypothesised, there was a reduction in propulsive power following lap 1, however, lap time remained unchanged. Presently, this was due to concurrent reductions in both brake work and brake time which effectively resulted in greater conservation of kinetic energy and further, an increased time spent travelling at higher speeds, which negated the time otherwise spent travelling slower. Practically speaking, reductions in both brake work and brake time were able to counterbalance a reduction in propulsive power. The observation of a maintenance in lap time during XCO-MTB is not new, and has traditionally been thought to be due to a superior ability to resist fatigue (Abbiss *et al.* 2013) or from athletes adopting an effective pacing strategy (Martin *et al.* 2012). However later, these interpretations were challenged by analysis of propulsive power data which showed a reduction across laps (Viana *et al.* 2013). The present investigation highlights that changes in braking could explain lap time maintenance displayed by XCO-MTB competitors, which ultimately points to some type of learning effect as laps are completed at race pace and warrants further investigation. It is important to note that all participants were allowed two laps for practice and warm up on the track used in this study, which may not have been enough to fully learn the track. Track familiarisation may affect pacing (Martin *et al.* 2012), however at present the interactions between the degree of familiarisation and braking is not fully understood.

The observations explained above allowed for better understanding of braking and propulsion to allow for the exploration of a performance-explaining linear regression model. As such, a combination of relative propulsive power, brake work, and brake time (Table 2) was used to determine their combined association with lap time. The resultant coefficient of determination (r^2=0.935) indicates that the variation in braking and propulsive variables is highly associated with lap time, and further, can explain variations in performance to within 3.3% error. To put this in to perspective, this braking/propulsive model explains variation in lap time better than relative propulsive power alone (r^2=0.826) on the track used in this study. Looking further in to what this model represents in the field, two riders who are equitable in terms of propulsive ability could complete contrasting XCO-MTB performances simply by braking for different durations or doing unalike amounts of brake work. Indeed, rates of propulsive work production do not always equate to XCO-MTB performance, which is an understanding that has led to novel approaches to gain better understanding of variations in race results. For example, while an intermittent power field test is significantly correlated to XCO-MTB performance (r^2=0.786) (Miller *et al.* 2014), the combination of peak power output, handgrip strength, and an XCO-MTB-specific decision-making task have proven more useful (r^2=0.970) (Novak *et al.* 2017). It should come as no surprise that sport-specific variables, in addition to physical fitness descriptors, can help understanding of variations in performance, however to date this has mostly been limited by the tools available. Therefore, the results of this study are promising and highlight that the use of a brake power meter is an exciting direction for future XCO-MTB investigations.

To provide a visual example of the interaction of braking and propulsive data, the readings recorded from one elite XCO-MTB rider on the first and third lap are highlighted with respect to the elevation profile in Figure 6.4A-B. The type of propulsive profile is commonplace for XCO-MTB, and supports the intermittent nature of the sport whereby there is a high rate of propulsive work on flat and ascending sections and reduced propulsive work on descents. Additionally, the braking profile is made clear—it can be seen that braking tended to coincide with lower levels of propulsive power, which tended to also be associated with descending sections. In this case, the braking is likely being done to control the speed of the bicycle, which is one component comprising of qualitative skill (Chidley *et al.* 2014). Some braking can also be noted in Figure 6.4A (lap 1) on flat and/or ascending sections, though most of these instances were reduced in Figure 4B (lap 3). Overall brake work and brake time were reduced in lap 3 by 9.2% and 4.6%, respectively; henceforth, these changes in braking counterbalanced a 6.7% reduction in propulsive power, as highlighted by less than 1% difference in lap time.

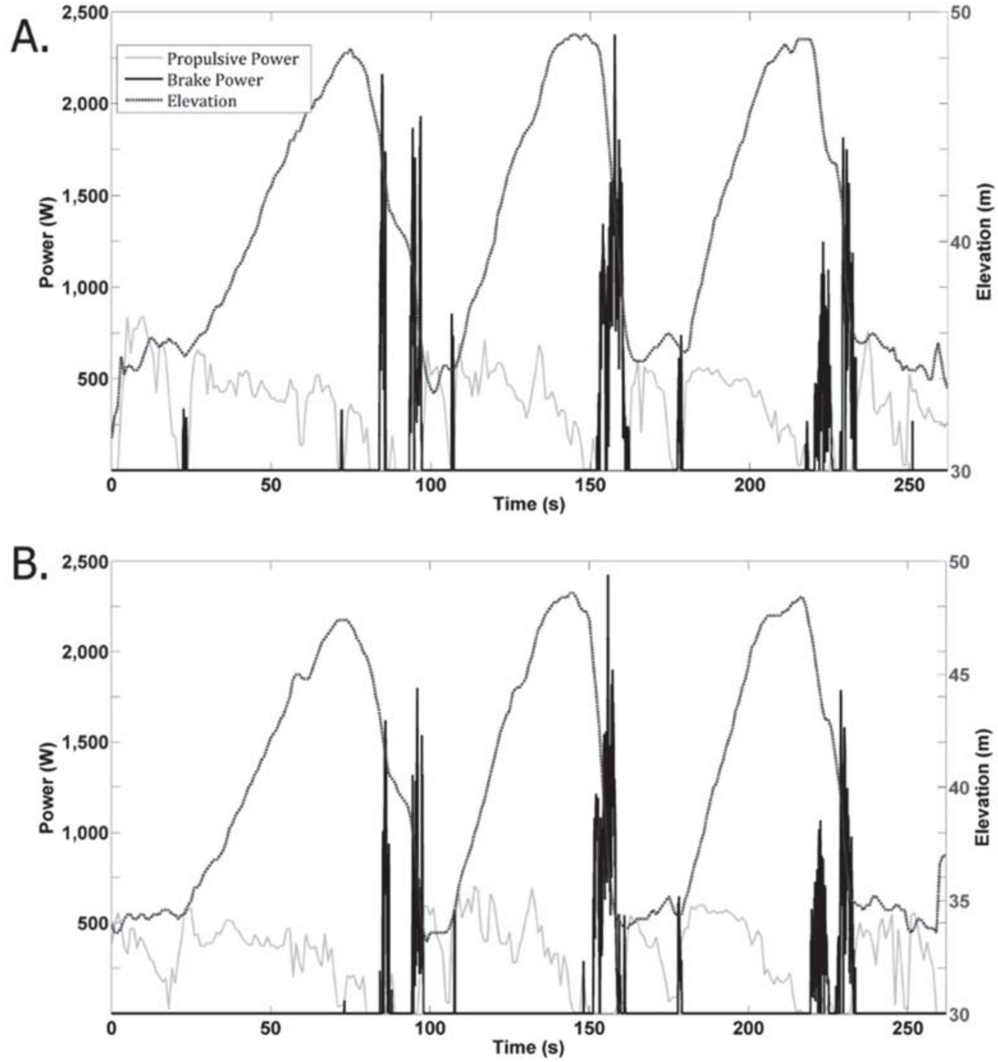

Figure 6.4. Example of braking and propulsive data for one participant on lap 1 (A) and lap 3 (B). The participant was a 22-year-old male weighing 68.5 kg with gear, had a VO2max of 73.1 ml/kg/min and was competitive in international races. For lap 1, braking variables were 20342 J, 28.3 s and 719 W for brake work, brake time and brake power, respectively. Average propulsive power was 328 W with resultant lap duration of 263.3 s. For lap 3, braking variables were 18461 J, 27.0 s and 683 W for brake work, brake time and brake power, respectively. Average propulsive power was 306 W with resultant lap duration of 263.8 s.

A limitation to the present investigation is the relatively short duration of the simulated time trial, which was due to battery power limits of the stand-alone data logger. Nevertheless, the length of the time trial was enough to see a reduction in propulsive power output across time which offered valuable insights on the interactions between braking and propulsion across a multi-lap time trial. Notably, the present investigation indicates the magnitude and importance of braking during XCO-MTB and display the data visually in a manner similar to practitioner software for propulsive variables. Future investigations should explore terrain-specific aspects of braking, with the ultimate goal of determining the extent that individuals can alter braking habits for increased performance.

6.6 Conclusion

The time spent braking is only a small portion of total lap time, however brake work rates are related to XCO-MTB performance. Riders reduce brake work and brake time as they become accustomed to riding a track at race pace, which is able to counterbalance a reduction in propulsive power. Variations in lap time can be explained by a combination of data collected with both a propulsive power meter and a brake power meter, and the data presented here indicate that future investigations exploring braking during mountain biking will offer greater resolution of cycling performance analysis.

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STATEMENT OF CONTRIBUTION
TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Matthew C Miller

Name/Title of Principal Supervisor: Prof Stephen R Stannard

Name of Published Research Output and full reference:

Quantification of brake data acquired with a brake power meter during simulated cross-country mountain bike racing (2017). Sports Biomechanics. IN PRESS.

In which Chapter is the Published Work: Chapter 7

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate: 90%

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Conceptualization; data collection and analysis; manuscript drafting and submission

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Chapter 7

MAGNITUDE DIFFERENCES IN BRAKING VARIABLES AND THEIR EFFECTS ON PERFORMANCE WHEN COMPARING EXPERIENCED AND INEXPERIENCED MOUNTAIN BIKERS NAVIGATING AN ISOLATED OFF-ROAD TURN

7.1 Abstract

Using a brake power meter, experienced and inexperienced mountain bikers were tested on an isolated, controlled off-road cycling descent with a turn to determine how riding experience affects the pattern of braking behaviour. Overall braking measurements such as absolute and relative brake work and brake power, as well as brake time, were significantly related to performance time on the track used in this study. Inexperienced mountain bikers displayed greater absolute and relative brake work and brake time, but had lower absolute and relative brake power when compared with experienced mountain bikers, which resulted in a significant performance decrement for inexperienced riders. Experienced mountain bikers concentrated braking efforts to later in the track, which meant that they spent less time at lower speeds. Inexperienced riders displayed a greater

reliance on the rear brake, which likely contributed to their overall increased braking variables. The results of this study highlight that differences in braking magnitude and behaviour are attributable to reduced performance on an isolated off-road track with a corner. Inexperienced mountain bike riders may be able to improve their performance by learning braking patterns similar to those of experienced mountain bikers.

7.2 Introduction

Olympic-format cross-country mountain bike racing features sections of high-intensity, low-speed ascents separated by lower-intensity, higher-speed or highly technical descents (Macdermid & Stannard, 2012). Ascending performance is appropriately attributed to aerobic and anaerobic energy production (Inoue *et al*. 2012; Impellizzeri & Marcora, 2007; Miller *et al*. 2014) and resultant mechanical propulsive work rates done through pedalling (Gregory *et al*. 2007; Prins *et al*. 2007). In contrast, descending sections are not dependent on propulsive power output (Hurst & Atkins, 2006) and have been shown to be linked with rider skill (Chidley *et al*. 2015). Given the multi-lap format of racing, XCO-MTB courses feature an equal amount of ascending and descending; however, due to the effects of gravity, more time is spent ascending within a race (Martin *et al.* 2012). Early pacing strategy descriptive studies of XCO-MTB competitions suggested that athletes focus on training aspects that will allow them to decrease the time spent on these ascending sections (Abbiss *et al.* 2013), though this overlooks the reduced ability to recover during descending sections due to vibration damping (Macdermid *et al*. 2014) and upper body work (Hurst *et al.* 2012). Henceforth, further investigations indicated that training should also address aspects that will allow competitors to decrease the time spent descending (Macdermid *et al*. 2016), but that these should not include an increase in pedalling which would exacerbate energy demand. Increasing speed on descents without adding pedalling can increase the rate of recovery before subsequent ascents, which could benefit overall performance (**Chapter 4**).

Until recently, methods to assess descending ability have remained qualitative (Chidley *et al.* 2014). However, a recently validated brake power meter may offer valuable non-propulsive cycling data (**Chapter 5**). One exploratory manuscript investigating XCO-MTB braking currently exists (**Chapter 6**); the significant negative association observed between brake power and lap time highlighted that the fastest riders were braking harder than slower riders, and further, spent less time using the brakes. Moreover, this study highlighted that competitors were able to reduce the brake work done and the time spent braking, which counterbalanced fatigue. In short, riders were able to change their braking habits to effectively navigate the track more efficiently. While this early study was promising in highlighting new technology, its exploratory nature lacked terrain-specific analysis and was a specific area the authors encouraged for future research. Especially useful would be the isolation of an area that requires braking, and to explore the differences demonstrated between faster and slower riders.

Based on visual inspection of the findings in the original study, one terrain-specific area to explore braking is on descents approaching turns. Specific braking strategies approaching turns are a well-accepted means of improving performance in motor sport racing (Casanova, 2000); however, the measured indices in motorsport are those which quantify deceleration patterns and brake pressure (Corno *et al*. 2008; Toyofuku *et al*. 1994) rather than brake power or brake work. Nevertheless, to maintain control of the vehicle while aiming for a minimum time to complete the section, braking should be completed before the turn starts, which is a strategy that aids in maintaining traction throughout the turn (Velenis *et al*. 2007). The same techniques have been taught for general mountain biking when the goal is to ride fast (Lopes & McCormack, 2005), with coaches subsequently instructing riders to "brake late and hard." These are two things implemented as much for control as they are for achieving overall minimum time, which is especially true given the often unstable surfaces ridden in XCO-MTB. The well-trained cohort in the original study also were able to utilise the front and rear brakes equally, which is one aspect of braking taught for maintaining control (Lopes & McCormack, 2005). Unfortunately, the best braking skills during turning manoeuvres are not inherent, and thus may be indicative of the degree of experience between riders.

Determining braking differences in groups of varying experience is important, as this may help indicate the degree of trainability for braking strategies. This is not indifferent to early explorative studies of physical fitness which indicated relative differences in propulsive power output (Lee *et al*. 2002). Indeed, it was crucial to first understand differences between the greatest and the least of cyclists, which in turn helped to understand traits that can be adopted to perform better; the same is now true for braking. Therefore, the aim of this study was to compare differences in braking variables between experienced and inexperienced mountain bikers on a controlled off-road track with a turn using a bicycle equipped with a brake power meter. It was hypothesized that more experienced riders would be able to complete the track faster than inexperienced riders, attributable to decreased time spent braking and increased braking power. The increased time spent braking by inexperienced riders was expected to extended the braking distance across sections of the track.

7.3 Methods

Participants

17 healthy cyclists (n=7 experienced, 85.83 ±12.67 kg; n=10 inexperienced, 95.99 ±10.77 kg) were initially weighed with cycling gear (clothing, helmet and shoes) and signed an informed consent that also detailed their mountain biking competitive experience. Participants were considered experienced mountain bikers if they rode off-road regularly (>3 times per week) and inexperienced if they did not cycle off-road regularly (<1 times per week).

Field test trials

All participants used the same bicycle (Trance 1, Giant Bicycles, New Zealand) with the chain removed, suspension inflated to maximum and mechanically locked-out, and tire pressure inflated to 0.34 psi/kg (Macdermid *et al.* 2014) of the total mass of the rider wearing cycling gear. The bike was outfitted with a proprietary brake power meter calibrated before testing according to previous studies (**Chapter 5**).

Participants completed three sequential trials on a closed test track (Figure 7.3; 77.60 m in length, 8.10 m of elevation loss), with the goal of completing the track as quickly as possible during each trial. The track was relatively short and incorporated a descent on forest road leading in to a 180º left-hand turn on grass, which was taped to 1.5 meters wide. The terrain was divided into four sections (A= 14.50 m; B= 35.80 m; C= 13.65 m;

D= 13.65 m) which allowed for the analysis of terrain-specific braking variables without depending on GPS data (Wing *et al*. 2005). Participants coasted from a standing start through sections A and B, which were downhill (-16% gradient) and delimited by a line across the track in fluorescent paint. To ensure that participants would begin braking at a similar speed, they were instructed to avoid braking within section A. Sections C and D made up a 180º left turn on flat ground and were split in half at the apex.

Data collection

Brake torque and angular velocity of the brake rotor were sampled at 128 Hz on a recently validated brake power meter and logged onto a stand-alone data logger (DI-710-UHS, DATAQ Instruments, Akron Ohio, USA). All equipment was manually zeroed or calibrated immediately before each testing session according to previously used guidelines (**Chapter 5**). Measurements of brake torque and wheel velocity were tranferred from the data logger onto a PC using proprietary software (WINDAQ Waveform Browser, DATAQ Instruments, Akron Ohio, USA), then transferred to LabChart 8.1.5 (ADInstruments Ltd, Colorado Springs Colorado, USA) for calibration. Raw values were collated using MatLab R2011b (The MathWorks, Inc., Natick, MA, USA) software and broken down for analysis. Similar to previous investigations, torques below 8 Nm were set to zero to reduce the effects of noise in the signal. Brake work (J) was calculated by integrating the product of brake torque and angular velocity for the two wheels summed together and for each wheel (front brake work for the front, rear brake work for the rear). The latter was also taken relative to the total mass of the rider plus cycling gear and the bicycle (relative brake work; J/kg). Brake time was calculated as the total time (s) per lap that either brake (front and rear brake time for front and rear brakes, respectively) or both brakes met or exceeded 8 Nm. Average brake power (W) was a product of brake work divided by brake time, and also calculated relative to the mass (W/kg) of the rider plus bicycle.

Statistical analyses

Analyses were completed using GraphPad Prism version 7.00 (GraphPad Software, San Diego California, USA). Average values of all variables recorded during the second and third trial were taken for analysis. The correlation coefficient was determined for the relationship with all braking variables and performance time. To determine gross differences between groups (Experienced or Inexperienced based on results from pre-trial questionnaire), unpaired student's t-tests were used to analyse the mass of rider plus gear, total time to complete the track, and variables of brake time, absolute and relative brake work and absolute and relative brake power. Due to differences in gradient—and thus speed and braking—of the terrain sections separated within the track, unpaired t-tests were also utilised to determine differences between groups in each section. To identify differences in front and rear brake usage between groups, two-way analysis of variance (ANOVA) was used to determine the interaction of group (e.g. Experienced or Inexperienced) *brake (e.g. front or rear) for overall values of relative brake work, brake time and relative brake power. For all analyses the significance level was set to $p<0.05$; actual p-values have been reported for ANOVA analysis.

7.4 Results

Overall investigations into braking variables identified that performance time was significantly related to brake work (3558.23 ±760.90 J; $r=0.582$), relative brake work (38.46 ±6.03 J/kg; $r=0.674$), brake time (5.10 ±1.51 s; $r=0.765$), brake power (736.16 ±167.81 W; $r=-0.669$), and relative brake power (8.03 ±1.92 W/kg; $r=-0.721$) (all $p<0.01$).

Importantly, between-group analysis identified there was no statistical difference ($t_{(15)}=1.78$, $p=0.0951$) in the mass of the rider plus cycling gear and bicycle. This resulted in no significant difference in the potential energy at the start of the trial (6820.48 and 7627.46 J; $t_{(15)}=1.78$, $p=0.0951$) or velocity (5.76 ±0.11 versus 5.91 ±0.22 m/s; $t_{(15)}=1.59$, $p=0.1327$) at the end of Section A for experienced and inexperienced groups, respectively, when coasting down the hill. Therefore, differences in braking variables between groups can be broadly attributed to the training status of respective groups rather than extraneous factors, and Section A was not included in section analysis. Between-group values and differences are highlighted in Table 7.1. Performance time analysis across the whole track revealed that experienced riders were able to complete the track significantly faster than inexperienced riders (13.88 ±0.54 versus 15.62 ±0.77; $p=0.0001$). Overall differences in braking variables between experienced and inexperienced groups included variables of brake work, relative brake work, brake time, brake power and relative brake power. Terrain-specific analyses for sections B-D (Table 7.1) highlighted significant differences in braking variables and performance time between groups in

Section B and Section C. Despite no difference in braking measurements, between-group differences in Section D were found for performance time. The velocity upon entering each section was different between groups in Sections C and D (Table 7.2). Similarly, there were differences for maximum velocity between groups in Sections B-D (Table 7.2).

Two-way analyses of front and rear brake utilization between groups (Figure 7.2A-C) identified a significant main effect of brake for brake time ($F_{(1,30)}$=8.54, p=0.0066) and relative brake work ($F_{(1,30)}$=5.93, p=0.0211). Significant interactions of group*brake were identified for relative brake work ($F_{(1,30)}$=12.04, p=0.0016) and brake time ($F_{(1,30)}$=12.80, p=0.0012). Post-hoc analysis revealed that the inexperienced group utilised significantly greater relative brake work (30.95 versus 9.64 J/kg, respectively; p=0.0004) and brake time (5.49 versus 1.69 s, respectively; p=0.0001) in the rear versus front brake. Similarly, rear relative brake work and rear brake time were significantly greater in the inexperienced group when compared with the experienced (13.19 J/kg, p=0.0273; 5.59 s, p=0.0226, respectively) group. Relative front brake power was greater in the experienced (6.64 W/kg) versus inexperienced (3.30 W/kg) groups, however there were no significant main effects or interactions for this variable.

Table 7.1. Mean ± SD of performance and braking variables between Experienced and Inexperienced mountain bikers.

Variable	*Group*	*Section B*	*Section C*	*Section D*	*OVERALL*
Performance Time (s)	Experienced	4.41 ± 0.16*	2.12 ± 0.20*	3.23 ± 0.32*	13.88 ±0.54*
	Inexperienced	5.14 ± 0.34	2.62 ± 0.30	3.68 ± 0.34	15.62 ±0.77
Brake Work (J)	Experienced	1374.13 ± 343.70*	1415.03 ± 409.31*	97.81 ± 71.08	2891.47 ±206.59*
	Inexperienced	2790.49 ± 480.82	1000.26 ± 357.50	107.01 ± 71.00	3905.01 ±578.72
Relative Brake Work (J/kg)	Experienced	16.41 ± 5.25*	16.71 ± 4.92*	1.16 ± 0.89	34.33 ±5.57*
	Inexperienced	29.12 ± 4.75	10.29 ± 2.95	1.11 ± 0.76	40.60 ±3.02
Brake Time (s)	Experienced	1.57 ± 0.79*	1.68 ± 0.46	0.23 ± 0.16	3.58 ±1.06*
	Inexperienced	3.67 ± 0.68	1.89 ± 0.33	0.29 ± 0.19	5.93 ±0.95
Brake Power (W)	Experienced	1009.73 ± 334.18	858.84 ± 180.47*	290.25 ± 121.55	864.49 ±195.77*
	Inexperienced	772.47 ± 115.44	527.67 ± 139.26	265.72 ± 108.57	670.83 ±116.92
Relative Brake Power (W/kg)	Experienced	11.82 ± 4.01*	9.98 ± 1.54*	3.33 ± 1.29	10.05 ±1.77*
	Inexperienced	8.07 ± 1.03	5.47 ± 1.19	2.72 ± 0.94	7.00 ±1.04

Note. ‘*’ signifies significant difference with Inexperienced group ($p<0.05$)

Table 7.2. Mean ±SD starting (Sections B-D) and maximum velocity (Sections A-D) for Experienced and Inexperienced mountain bikers.

Variable	*Group*	*Section A*	*Section B*	*Section C*	*Section D*
Starting Velocity (m/s)	Experienced	*n/a*	5.76 ±0.01	7.62 ±0.44*	5.28 ±0.35*
	Inexperienced	*n/a*	5.91 ±0.05	6.14 ±0.34	4.26 ±0.16
Maximum Velocity (m/s)	Experienced	6.22 ±0.03	9.79 ±0.30*	7.95±0.28*	5.71 ±0.54*
	Inexperienced	6.19 ±0.01	8.12 ±0.27	6.52 ±0.41	4.52 ±0.21

Note. ‘*’ signifies significant difference with Inexperienced group ($p<0.05$)

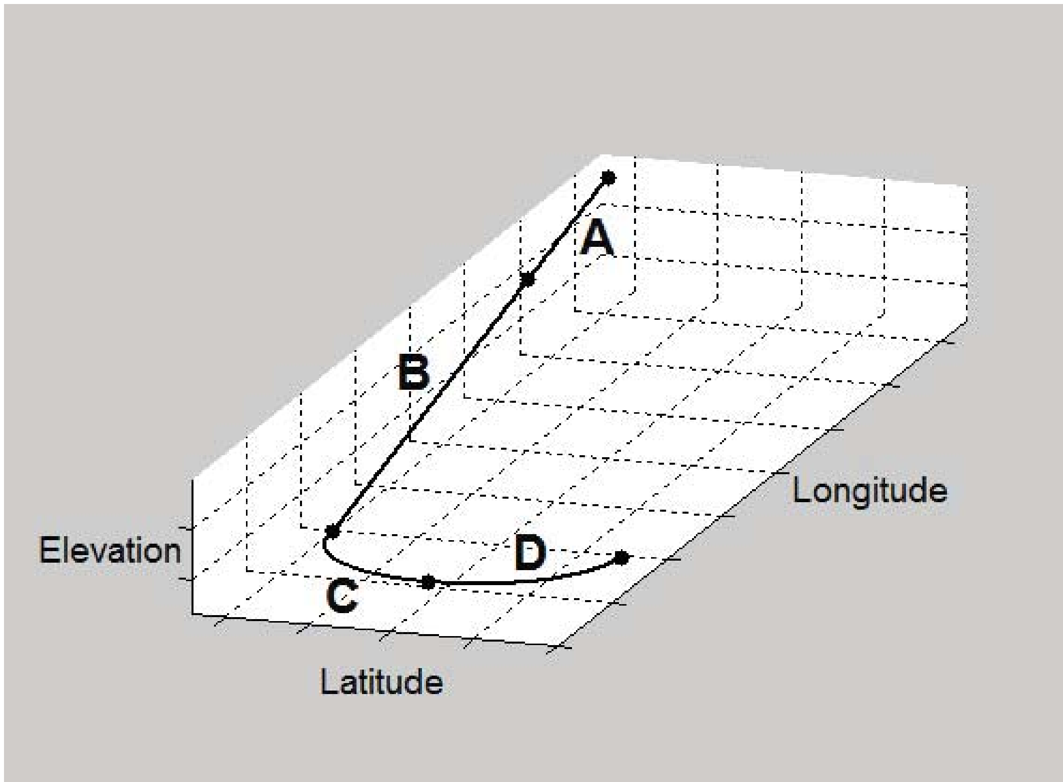


Figure 7.1. Schematic representation of the off-road track and turn highlighting profiles for terrain sections (A-D= distance, gradient; A= 14.50 m, -16%; B= 35.80 m, -16%; C= 13.65 m, 0%; D= 13.65 m, 0%), which were measured with a trundle wheel. Black dots represent boundary for each section.

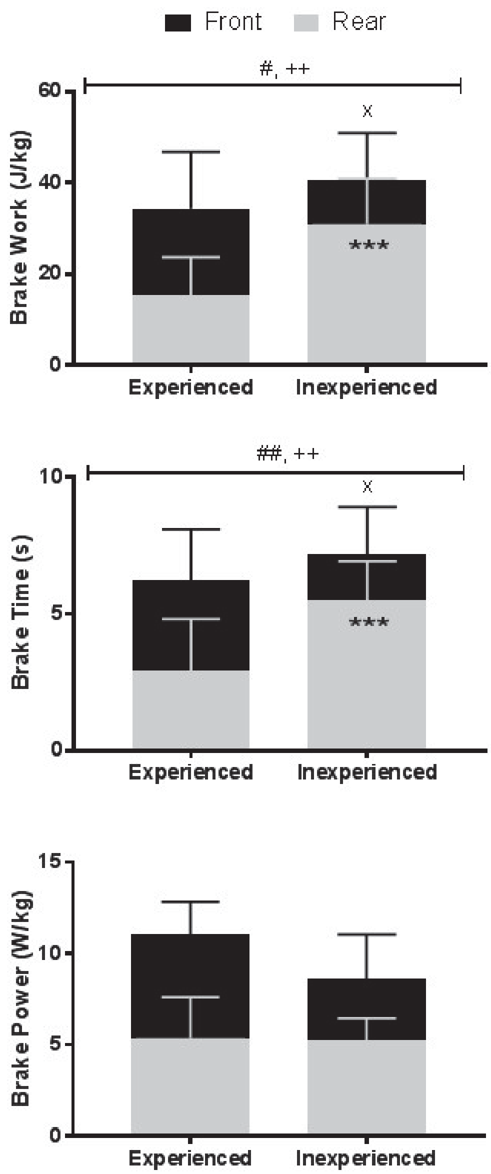


Figure 7.2. Two-way analyses for relative brake work (J/kg; A), brake time (s; B) and relative brake power (W/kg; C) for Experienced and Inexperienced groups.

'#' signifies main effect of brake ($p<0.05$), '##' ($p<0.01$); '++' interaction between group*brake ($p<0.01$).

Post-hoc differences: '***' significant difference with front brake ($p<0.001$); 'x' significant difference with inexperienced group ($p<0.05$).

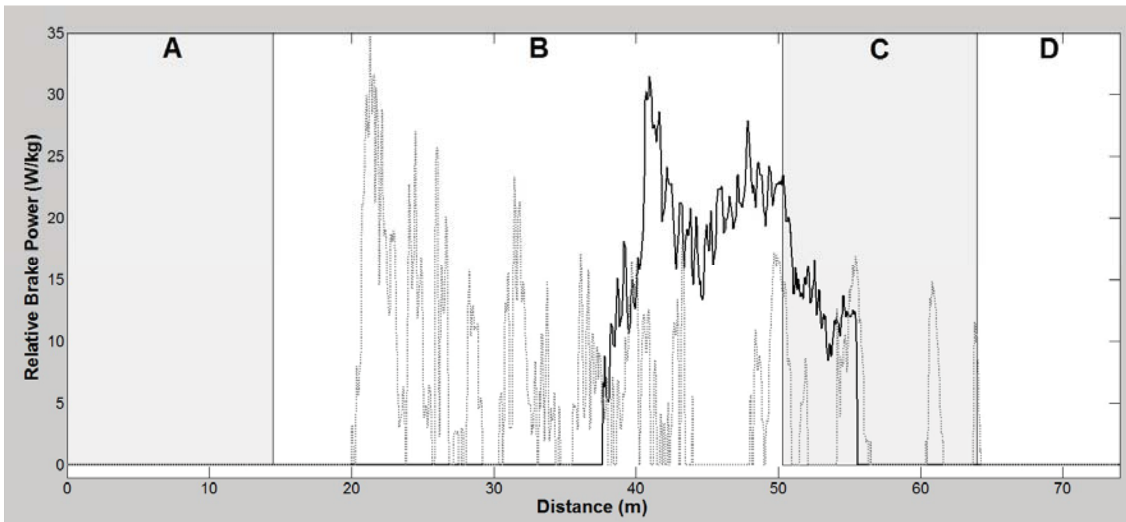


Figure 7.3. Example trace of relative brake power of one experienced (black) and one inexperienced (grey) riders throughout respective (A-D) sections of the track. The respective mass of each rider (plus cycling gear) was not overly dissimilar (63.6 and 64.8 kg, respectively). Relative brake work, brake time, and relative brake power were 33.36 J/kg, 2.46 s, and 13.57 W/kg for the experienced and 37.16 J/kg, 4.53 s, and 8.21 W/kg for the inexperienced rider, respectively. Individual braking strategies elicited performance time of 14.08 and 15.87 s for the experienced and inexperienced rider, respectively.

7.5 Discussion

The aim of this study was to quantify the magnitude of differences in braking variables for experienced and inexperienced mountain bikers on a controlled off-road turn and to determine where within a track braking differences may occur. It was hypothesized that inexperienced riders would do more braking than experienced riders, which would result in increased time to negotiate the corner. The increased braking was expected to extend the distance of the braking, which would become evident in sectional analysis. The main findings of this study are: a) experienced riders are able to complete an off-road turn in less time and with a greater maximum velocity than inexperienced riders, which is attributed with decreased brake work and brake time, and increased brake power; b) braking variables were significantly different between groups in early and mid-sections of the turn (sections B and C), which resulted in an increased performance time and lower maximum velocity for the inexperienced group in all sections (sections B, C and D); and c) inexperienced riders are more reliant on the rear brake than experienced riders, which contributed to increased overall braking.

Not surprisingly, the data indicate that braking variables are strongly related to performance time on a short descending track ending with a corner. Similar to results previously reported (**Chapter 6**), absolute and relative brake power and brake time were significantly related to performance time on this track. The nature of the track used in this study also highlighted that absolute and relative brake work were related to performance time, which may be attributed to the brevity of the track and the strictly downhill or flat features (i.e. no ascending or dependence on propulsive power as previously investigated) and was not shown previously. The directions of the correlations are important to note; a decrease in brake work and brake time—but increase of brake power—were significantly related to performance time. The correlations were supported by braking variables analysed by group (Table 7.1; OVERALL), which helped to explain differences in performance; indeed, inexperienced riders displayed increased brake work and brake time, but decreased brake power across the track used in this study. The overall use of the brakes by experienced riders in this study support practitioner publications that encourage braking hard and spending as little time braking as possible (Lopes and McCormack, 2005).

The initial braking report highlighted decreased brake time and brake work could counterbalance performance decrement caused by physical fatigue (**Chapter 6**). However, that study lacked the resolution needed to understand braking and performance variables independent of propulsive power, which are addressed in the present study. By isolating and controlling a small track and partitioning it into sections, braking and performance variables analysed by group offered a greater insight into *where* and *how* riders of different abilities use their brakes. Table 7.1 highlights braking differences in Sections B-D, indicating that experienced riders waited until further along the track to brake. To achieve this performance, experienced riders did less brake work in Section B—but greater brake work in Section C—when compared with inexperienced riders, which supports a late-braking strategy (Lopes & McCormack, 2005). This strategy resulted in higher maximum velocity for experienced riders in Sections B-D (Table 7.2). The late braking strategy continued to benefit the experienced group throughout Sections C-D, which is evident in the difference in performance time between groups (Table 7.1) and the higher velocity upon entering each section for the experienced group (Table 7.2). Importantly, the performance time difference noted in Section D is independent of braking; the experienced group was able to complete Section D faster than the inexperienced group due to the braking strategy in preceding sections and the increased velocity at the start of this section. The effect of braking on performance can be explained by inexperienced riders spending more time at lower speeds due to excessive braking and is mainly linked with reduced relative brake power. Of course, a braking strategy of braking late and hard is commonplace in motorsports (Corno *et al.* 2008) and not new in MTB (Lopes and McCormack, 2005); however, this is the first time these measurements have been shown in the literature. It's worth noting that while the best braking strategies in motorsports highlight that no braking should be done once turning starts, experienced riders in this study still did a considerable amount of braking in the turn (Section C); this may be attributable to the relatively long and gentle arc of the turn but is worth further investigation.

Figure 7.3 highlights the magnitude and location differences of braking between groups, with more temporally concentrated braking in experienced riders. For the sake of this sole visual comparison, riders of similar mass were selected, which allows easy comparison of relative brake power readings. It is this type of visual inspection that coaches will often first utilise when trying to understand athlete's propulsive power output (Allen & Coggan, 2012), whereby the location and magnitude of pedalling becomes apparent; henceforth, recommendations to improve performance can be drawn. Therefore, given the findings of this study and the data presented in Figure 7.3, the coach may implement an intervention to modify the inexperienced rider's braking to further down the track, which will have a positive effect on performance time. Future research should investigate brake strategy implementation methods as the present investigation highlights the importance of braking strategy.

Finally, we investigated differences between experienced and inexperienced riders by the brake used as a mean throughout the track (Figure 7.2). This was of interest because of the safety implications of relying on one brake versus the other. Practitioner publications suggest to avoid locking the front wheel and to brake with both brakes evenly in an effort to maintain control (Lopes and McCormack, 2005), which seems intuitive. Similarly, in *The Art of Mountain Biking* (2012), the author describes situations in which an overly used rear brake can cause the wheel to lose traction. Two-way analyses (Figure 7.2) indicated that experienced riders did not use the front and rear brakes differently, which may have contributed to a sensation of greater control. Conversely, inexperienced riders were more reliant on the rear brake, which may have negatively affected this group's sense of control of the bicycle. The non-significant difference in front brake values between groups indicates that over-braking in the rear by inexperienced riders contributed to overall increased braking and affected this group's ability to navigate the track as quickly as experienced riders. Considering all observations from this study, we can surmise that reduced use of the rear brake could reduce overall brake work and brake time, which would benefit performance.

This study is the first to directly indicate the differences in braking of experienced and inexperienced mountain bike riders navigating a controlled off-road track. The results presented here enhance previous investigations by focusing on a controlled, isolated track with instances of concentrated braking efforts. While controlling the line that riders could take in this investigation, we removed some of the practicality of XCO-MTB, per se; however, results clearly indicate differences in performance attributable to differences in braking. Current technology renders some manoeuvres of the bike unquantifiable, though braking can, in the future, be one area on which there could be more focus. Future research should investigate the trainability of braking strategy specific to XCO-MTB, particularly on off-road tracks.

7.6 Conclusion

Inexperienced riders performed more poorly than Experienced riders, which was attributable to differences in braking. Lower-performing riders could perform more like better-performing riders by concentrating braking efforts at a later point for overall reduced brake work and brake time, but increased brake power. Reduced reliance on the rear brake my positively affect overall brake work and brake time, which should benefit performance. More research is needed on proper off-road cycling tracks, and should include propulsive variables in addition to braking.

Chapter 8

CALCULATION OF REAR BRAKE POWER DURING SKIDDING IN ROAD AND OFF-ROAD CYCLING CONDITIONS

8.1 Abstract

The use of a brake power meter at each wheel of a bicycle is a valid means to calculate energy losses due to braking. However, methodology utilizing the torque and angular velocity at each wheel independently are not able to reflect energy lost to braking when the rear wheel is skidding. This study tested the possibility of using the angular velocity of the front wheel, but the torque of the rear brake, to calculate rear brake power. One experienced cyclist completed 34 braking trials on a mixture of road and off-road surfaces with a mixture of skidding and non-skidding. The total energy removed from the bicycle-rider system was adjusted utilising the calculation at question and added to estimates of drag and rolling resistance. This adjusted energy removed displayed a strong positive relationship with the change in kinetic energy of the bicycle-rider system during braking (r^2=0.947; p<0.0001). These findings indicate that rear brake work is underestimated when using the angular velocity at the rear wheel during skidding, but that utilising the angular velocity of the front wheel is a valid means of calculating rear brake power.

8.2 Introduction

A bicycle brake power meter has recently been validated that can measure the rate of energy removed from the bicycle rider system through the rider-induced interaction between the brake caliper and the rotor (**Chapter 5**). This brake power meter has since been utilised to calculate the brake work and rate of brake work (braking power) during actual cycling (**Chapter 6**; **Chapter 7**). These investigations henceforth indicated the importance of describing and understanding braking patterns during XC Mountain Bike cycling, and supported the idea that braking did indeed affect cycling performance.

During these analyses, there were no instances recorded of the front wheel locking up or the front tire skidding, which was apparent by inspection of angular velocity at the front wheel. This observance supported practitioner philosophies which contend that locking the front wheel results in losing control of the bicycle (Lopes & McCormack, 2010). Occasionally however, the rear wheel brake was locked which resulted in the skidding of the rear tire. This equated to 1.1 s per lap on a 1.24 km cross-country mountain bike race track (**Chapter 5**). While the benefits or detriments of skidding and performance are not well-understood, previously described methods (**Chapter 5**; **Chapter 6**; **Chapter 7**) utilised to calculate brake power were not able to account for friction-related energy losses experienced when the rear wheel is skidding.

Brake power is calculated at each brake as the product of brake torque times the angular velocity of the wheel given,

$$\text{Brake power} = \tau * \omega \qquad \text{(Eq. 8.1)}$$

Where, τ is torque and ω is angular velocity.

In this case, any time the wheel stops spinning, the resultant power is 0 W despite any recorded torque. However, it is obvious that energy is being removed from the bicycle-rider system during skidding, being converted to heat, noise, and physical work done on the terrain surface. Therefore, to ensure accurate brake power and work readings, this energy loss must be accounted for.

Since Eq. 8.1 is not accurate for calculating brake power during skidding, it may be possible to calculate brake power as the product of force and velocity instead. In this case a combination of measurements from both the front and rear wheels can be utilized due to them both being connected to the same bicycle.

If we assume that the front wheel does not skid, the velocity of the bicycle can be calculated by measuring the angular velocity of the front wheel given,

$$v = \omega_f * r \qquad \text{(Eq. 8.2)}$$

Where, v is velocity, ω_f is the angular velocity of the front wheel, and r is the radius of the front wheel.

To be able to calculate the energy lost in skidding we must calculate the frictional force at the tyre-terrain interface. This force can be calculated given,

$$F = \frac{\tau_r}{r} \qquad \text{(Eq. 8.3)}$$

Where, F is the frictional force between the skidding tire and the ground, τ_r is the torque at measured at the brake of the rear wheel and r is the radius of the rear wheel.

Therefore, since power is the product of force and velocity,

$$F * v = \frac{\tau_r}{r}(\omega_f * r) \qquad \text{(Eq. 8.4)}$$

This can be simplified to,

$$\text{Brake power} = \tau_r * \omega_f \qquad \text{(Eq. 8.5)}$$

While Eq. 8.5 is theoretically valid, it is not currently known if this calculation will provide valid rear brake power recordings during actual field use. Therefore, the aim of the present study was to determine the validity of brake power measurements during skidding by adjusting brake power measurement to the product of brake torque at both the front and rear wheels, but measuring angular velocity at only the front wheel.

It was hypothesized that the adjusted brake work calculated during braking events with skids and without skids would be strongly associated with the change in kinetic energy of the bicycle-rider system on both road and off-road surfaces.

8.3 Methods

One cyclist (eight years cycling experience; 178 cm; 85.04 kg) completed 34 braking trials on a mixture of dirt and tar-sealed flat roads while riding a bicycle outfitted with a brake power meter. All braking was done while coasting in a straight line with the participant seated on the saddle. The participant was instructed to complete a mixture of skids and non-skids, but given no limitation on how to brake otherwise; this ensured that there was a mixture of front and rear brake utilization and importantly, several non-skidding events to add into the analysis.

Data was sampled at 128 Hz and collected on a stand-alone data logger. Data files were converted to *.mat format and transferred to Matlab R2011b for analysis. Non-adjusted rear brake power was calculated as the product of rear brake torque and the angular velocity of the rear wheel, while adjusted rear brake power was calculated in accordance with Eq. 8.5. Front brake power was calculated as the product of front wheel angular velocity and front brake torque. Non-adjusted brake work was calculated by integrating the product of the sum of front brake power and rear brake power, while adjusted rear brake work instead incorporated adjusted rear brake work. To calculate the total energy removed from the bicycle-rider system, estimates of aerodynamic drag and rolling resistance were added to brake work, where adjusted energy removed calculated rear brake power using Eq. 8.5. Adjusted and non-adjusted total energy removed were compared with the change in kinetic energy given,

$$Brake\ work + E_{rr} + E_d = \Delta E_K \qquad \text{(Eq. 8.6)}$$

Where, E_{rr} is rolling resistance, E_d is aerodynamic drag and is the change in kinetic energy, which were calculated according to our previous work (**Chapter 5**).

Skidding work was calculated as the difference in adjusted and non-adjusted rear brake work.

All analyses were completed using GraphPad Prism 7.00, with the alpha value set a 0.05.

8.4 Results

Mean ± SD and range of braking data are highlighted in Table 8.1. Non-adjusted and adjusted (for skidding) energy removed from the bicycle rider system were significantly different from each other ($t_{(33)}$=5.98; $p<0.0001$) and this was associated with a significant difference in non-adjusted and adjusted rear brake work ($t_{(33)}$=6.06; $p<0.0001$). This shows the importance of being able to account for skidding in calculating braking work and thus power. In terms of validation of the derived equation for calculating total braking power (including skidding), the coefficient of determination between the change in kinetic energy and adjusted energy removed during braking was r^2=0.947 ($p<0.0001$; Figure 8.1).

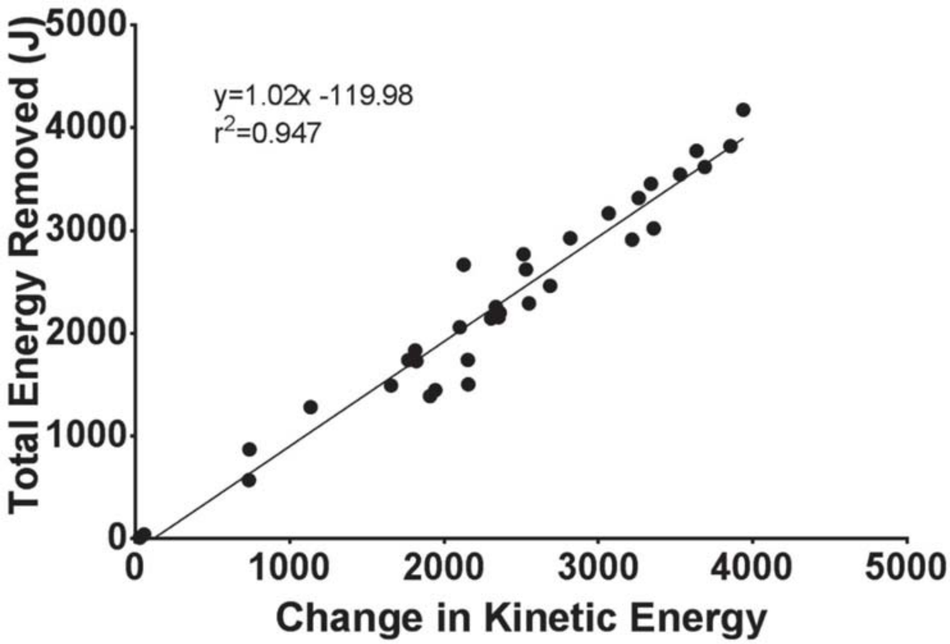


Figure 8.1. Correlation between the change in kinetic energy and adjusted energy removed from the bicycle-rider system.

Table 8.1. Mean ± SD and range for calculated variables of energy loss during braking.

Variable	Mean	SD	Minimum	Maximum
Distance (m)	6.2	3.0	0.2	11.3
Duration (s)	3.7	1.4	0.3	6.2
Rolling resistance (J)	136.0	65.6	3.6	246.7
Aerodynamic drag (J)	24.1	16.5	0	52.5
Front brake work (J)	781.4	1005.1	0	2878.5
Rear brake work, non-adjusted (J)*	273.7	169.3	0	622.3
Rear brake work, adjusted (J)*	1323.3	1123.4	0	3523.1
Skidding work (J)	1049.5	1010.1	0	3061.9
Total energy removed, non-adjusted (J)	1191.24	999.0	0	3667.0
Total energy removed, adjusted (J)	2264.7	1054.8	9.4	4175.3
Change in kinetic energy (J)	2337.3	1006.3	27.9	3938.5

Note. Values were obtained from 34 braking events on a mixture of flat, tar-sealed road and a flat dirt path. * signifies a significant difference ($p<0.0001$).

8.5 Discussion and Implications

The aim of this study was to validate a method to calculate the energy losses during rear wheel skidding on a bicycle equipped with a brake power meter. Rear brake power was calculated in two ways; non-adjusted rear brake power was calculated using rear-wheel-only measures while adjusted rear brake power was calculated as a product of rear wheel torque and the angular velocity of the front wheel. It was hypothesized that the adjusted total energy removed from the bicycle-rider system would not be different than the change in kinetic energy of the bicycle-rider system, and that the two measurements would have a strong correlation. The findings of the present investigation support the hypothesis on both road and off-road surfaces across a range of speeds (Figure 1).

The magnitude of work done during skidding is significant, and cannot be calculated using previously published brake power calculation (**Chapter 5**). Given these findings, rear brake work is underestimated when utilizing previously used power calculation at independent wheels during skidding (Table 8.1). It is recommended that future research should utilize the adjusted rear brake power calculation to appropriately asses braking during real cycling.

8.6 Limitations and Conclusion

A limitation to the present investigation is the low sample size of braking events. This is indeed the case when compared with the original manuscript which incorporated over 400 braking events. However, the present investigation sought not to validate the device but to validate the calculation of adjusted rear brake power. Given that the device has undergone validation on both road and off-road surfaces and the similarity between the present and past findings, the authors did not believe that more skidding samples were necessary.

The present findings highlight that brake power can be calculated as the product or rear wheel torque and the angular velocity of the front wheel, which is able to reflect the energy losses during skidding. To accurately assess energy loss due to braking during real cycling experience, the authors suggest that rear brake power be calculated as at present. In the future, it is likely important to quantify of the amount of work done through skidding during real cycling.

Chapter 9

VALIDATION OF A NORMALIZED BRAKE WORK ALGORITHM DESIGNED TO OUTPUT A SINGLE METRIC TO PREDICT NON-PROPULSIVE MOUNTAIN BIKE PERFORMANCE

9.1 Abstract

The interaction between variables such as brake work, brake time and brake power can be somewhat complicated, which might be a barrier to the utility of the brake power meter as a training tool for mountain biking. The aim of this study was to determine if brake power can be normalized to create a single-metric output more strongly related to mountain bike descending performance. Nine nationally competitive mountain bikers completed three trials each at race pace on a mountain bike descent using a bicycle equipped with a brake power meter. Brake power was normalized instantaneously by dividing it by the kinetic energy of the bicycle-rider system, and was integrated to calculate normalized brake work. Normalized brake work (26.3 ±15.3) was more strongly associated (r^2=0.929; p<0.0001) with descending performance time (130.8 ±20.1 s) than relative brake work (676.0 ±152.3 J/kg; r^2=0.477; p<0.0001), brake time (62.3 ±21.1; r^2=0.729; p<0.0001) or relative brake power (11.4 ±2.2 W/kg; r^2=0.429; p=0.0002). On

the descent used in this study, normalized brake work was the strongest indicator of descending performance based on braking. It is recommended that this metric be used to quickly assess brake use, and that further analysis be done to fine-tune braking strategy.

9.2 Introduction

Data gathered from propulsive power meters have been reasonably straight-forward for describing the variance in ascending cycling performance. Relative rates of propulsive work have a strong negative association with ascending ability, which means that to reduce time on uphill sections, competitors must aim to increase rates of relative propulsive work (i.e. relative propulsive power; W/kg). Accordingly, there has been a lot of focus in the literature aimed at training interventions to increase relative propulsive power.

While propulsion remains an important factor determining Olympic format cross-country mountain bike racing (XCO-MTB) performance, new evidence utilising a brake power meter has highlighted the importance of braking (**Chapter 5**; **Chapter 6**; **Chapter 7**). Firstly, by employing a combination of propulsive and braking variables, variances in XCO-MTB lap time were well-explained. Soon after, it was discovered that performance time on a short descent is significantly associated with measurements of relative brake work, brake time, and relative brake power (r^2=0.34-0.59), which was the first attempt at quantifying descending performance. It was also surmised that inexperienced XCO-MTB riders display different braking patterns than experienced riders. Therefore, for riders to perform better, appropriate brake training strategies could be developed to intervene in poor braking habits. However, the magnitude of braking necessary to slow riders down is dependent on a number of variables, which complicates the interaction between brake work, brake time and brake power. This means that neither one variable is great at explaining the variances in descending performance, which may be a barrier to the ease of brake training administration and descending performance explanation.

To highlight some of the complexities of brake data analysis, simple energy equations can be utilised to compare braking data and effects on performance given the *law of conservation of energy*. At the same time, these same equations may also help to reduce brake power meter data to more usable and comparable metrics.

Firstly, brake work is equal to the change in kinetic energy when accounting for drag and rolling resistance given,

$$Brake\ work + E_{rr} + E_d = \Delta E_K \quad \text{(Eq. 9.1)}$$

where, E_{rr} is rolling resistance, E_d is energy lost to aerodynamic drag, and ΔE_K is the change in kinetic energy. In the case of brake power meter utilisation, brake work is of interest in Eq. 9.1; other energy loss calculations were explained previously (**Chapter 5**). Nevertheless, the above calculation represents that brake work and kinetic energy are easily compared with each other.

The change in kinetic energy of the bicycle-rider system can be explained given,

$$\Delta E_K = \left[\left(\frac{1}{2}mv_2^2\right) - \left(\frac{1}{2}mv_1^2\right)\right] + \left[\left(\frac{1}{2}\mathrm{I}\omega_2^2\right) - \left(\frac{1}{2}\mathrm{I}\omega_1^2\right)\right] \qquad \text{(Eq. 9.2)}$$

where, *m* is the combined mass of the rider wearing cycling gear and the bike, *v* is the average velocity, I is the moment of inertia, and ω is the angular velocity of the front wheel.

The instantaneous kinetic energy can therefore be calculated as,

$$\mathrm{E_K} = \left(\frac{1}{2}mv^2\right) + \left(\frac{1}{2}\mathrm{I}\omega^2\right) \qquad \text{(Eq. 9.3)}$$

where, *v* and ω are instantaneous velocity and angular velocity, respectively.

In Eq. 9.3, *m* and *v* are important to note: firstly, assuming two riders of different mass, the kinetic energy at any given time is not equal. More importantly, two riders of the same mass but travelling at different velocities, will have quite different kinetic energy because this value is proportional to velocity squared. In these two cases, the brake work required to bring the riders to a stop is not equal and thus indicates the complexity of brake power meter analysis. Indeed, with differences in the amount of brake work required, metrics of brake time and thus brake power are skewed accordingly, which explains the relatively weak association with these traditional brake measures and descending performance. This potential barrier to the understanding and comparison of the data must be overcome for brake power meter measurements to have utility for training.

With this in mind, it is sensible to develop an algorithm that can calculate the amount of braking done by the rider in relation to both the total mass and the velocity of the bicycle-rider system. Such a metric would indicate the extent to which the braking is affecting progression along the trail and reflect the efficiency at which the rider can negotiate the descent. One way to do this could be to calculate the instantaneous brake power as a percentage of the kinetic energy of the bicycle-rider system. This normalization of brake power would eliminate the complexity of brake power being scaled by mass and velocity. Then, normalized brake power can be integrated to account for the time component of input to the brakes. The result of this integration would henceforth be normalized brake work, ultimately outputting a single metric to describe the descending performance of the rider based on braking. Therefore, this study set out to determine the validity of an algorithm designed to calculate normalized brake work. It was hypothesized that variations in performance time on a mountain bike descending track could be better explained by brake readings reduced to normalized brake work than by traditional brake metrics of relative brake work, brake time, or relative brake power, henceforth signifying the validity of the algorithm at question.

9.3 Methods

Nine nationally competitive mountain bikers (mean ± SD: age= 25.6 ±3.6 years; body mass= 77.4 ±11.6 kg; height= 177.2 ±11.2 cm) volunteered for this study which was approved by the primary university's Human Ethics Committee. Participants all rode the same mountain bike (Trance 1, Giant Bicycles, New Zealand), which had suspension adjusted to manufacturer specifications pre-testing and had tires inflated to a standardized pressure (Macdermid *et al*. 2014). The bike was outfitted with a brake power meter that continuously sampled and recorded at 128 Hz, and a propulsive power meter (S2275, Quarq, Spearfish, SD, USA) that output data at 1 Hz (**Appendix I & II**). Both units were calibrated using two-point and one-point calibration, respectively, preceding testing. Brake power meter data (brake torque and angular velocity of the rotor at each wheel, respectively) were recorded on a data logger (DATAQ UHS710; DATAQ Instruments, Akron Ohio, USA) attached to the bicycle handlebars while propulsive power was recorded on a portable cycle computer (510; Garmin Ltd., Schaffhausen, Switzerland). The total mass of the bicycle and all equipment was 18.64 kg.

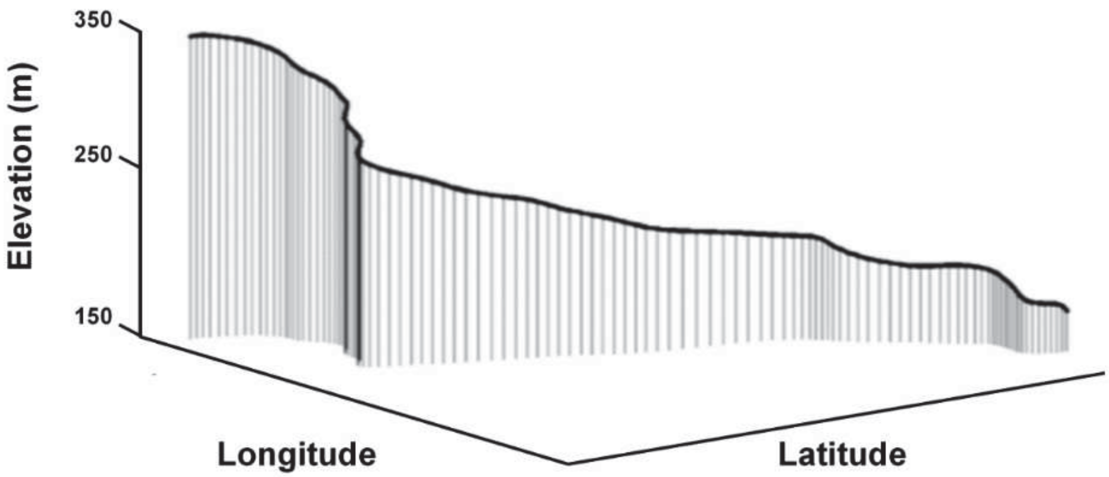


Figure 9.1. Elevation profile of the descending track used for testing in this study. The total distance was 1.01 km with a total elevation loss of 165 m (average gradient of -16.3%). This track was chosen based in its previous use which indicated that performance time was not dependent on propulsive work.

Prior to testing, each participant was weighed while wearing cycling apparel, which included clothing, helmet and shoes. On arrival to the mountain bike park, each participant completed a 30-minute warmup on the bicycle, which also served as a familiarization of the equipment. Participants then underwent three test trials at race pace on a mountain bike descent (Figure 9.1) that was chosen because of its descending nature which eliminated performance benefits due to pedalling (**Chapter 5**). All participants were given 15 min epoch between trials.

Brake power meter data was converted to *.mat files in accordance with previous investigations and Matlab R2011b (The MathWorks, Inc., Natick, MA, USA) was used to calculate variables of interest. Performance time (s) to complete the descent was determined by integrating the velocity of the front wheel across the distance of the track which allowed the determination of performance without relying on GPS data. Front brake power (watts) was calculated as the product of front wheel torque and the angular velocity of the front wheel. Rear brake power (watts) was calculated as the product of rear wheel torque and the angular velocity of the front wheel, which has recently been validated as a method to measure rear brake power and calculates for the frictional forces of the tire during skidding. Any measurement that did not exceed 8 Nm was removed from analysis to reduce the effect of noise. Brake work (joules) was calculated by integrating the product of front and rear brake power across the duration of the track, and was reported relative to the mass of the rider wearing cycling gear plus bicycle (joules/kg). Brake time (s) was the total time that either brake exceeded 8 Nm. Relative brake power (watts/kg) was calculated as the product of relative brake work divided by brake time.

Normalized brake power was calculated instantaneously given,

$$\text{Normalized brake power} = \frac{\text{Brake power}}{E_K} \qquad \text{(Eq. 9.4)}$$

where brake power and E_K are instantaneous. The units for normalized brake power are in Hz (1/s) since the calculation divides a rate of work (i.e. power) by work (i.e. kinetic energy).

Normalized brake power was integrated to calculate normalized brake work across the descent given,

$$\text{Normalized brake work} = \int_0^t \text{Normalized brake power} \qquad \text{(Eq. 9.5)}$$

where normalized brake work has no unit since it is a frequency which has been integrated over time.

Propulsive work on the descent used for testing was not a performance benefit factor, but was calculated by multiplying the average power output collected onto the Garmin device by the performance time of each trial. The potential energy of the descent was calculated for each participant as the product of the mass of the bicycle-rider system times the height of the descent (165 m) and gravity (9.81 m/s^2). Due to minimal propulsive work, the increase in kinetic energy on the descending track utilized was proportional to the reduction in potential energy throughout the descent. This meant that no two participants had vastly differing opportunities to gain velocity outside of differences in braking, which gives the normalized brake work algorithm sound theoretical validity for use presently.

Statistical analyses

Each of the 27 descent trials completed by the nine participants were included in analysis. All statistical analyses were completed in GraphPad Prism 7.00 (GraphPad Software, San Diego California, USA). The mean ± standard deviation (SD) was calculated for performance time, relative brake work, brake time, relative brake power and normalized brake work across all trials. The coefficient of determination was calculated between performance time and normalized brake work, relative brake work, brake time and relative brake power, respectively, for all trials completed on the mountain bike descent. The alpha value was set to 0.05.

9.1 Results

The potential energy at the onset of the descent was 154,578 ±18,887 J, and participants completed an average propulsive work equating to 1,231 ±3,217 J. Descriptive data for performance and braking variables are highlighted in Table 9.1. The relationship between performance time and relative brake work, brake time, relative brake power and normalized brake work, respectively, are reported in Figure 9.2A-D. Normalized brake work on the track used in this study displayed the strongest relationship with performance time ($r^2=0.929$, $p<0.0001$). Normalized brake work was also significantly related to traditional measurements of relative brake work ($r^2=0.669$, $p<0.0001$), brake time ($r^2=0.799$, $p<0.0001$) and relative brake power ($r^2=0.293$, $p=0.0036$).

Table 9.1. Mean ± SD for performance and braking variables.

Variable	Mean	SD
Performance time (s)	130.8	20.1
Velocity (km/h)	28.4	3.8
Relative brake work (J/kg)	676.0	152.3
Brake time (s)	62.3	21.1
Relative brake power (W/kg)	11.4	2.2
Normalized brake work	26.3	15.3

Note. Values were obtained from 27 descending trials on a mountain bike track that was not dependent on propulsive work

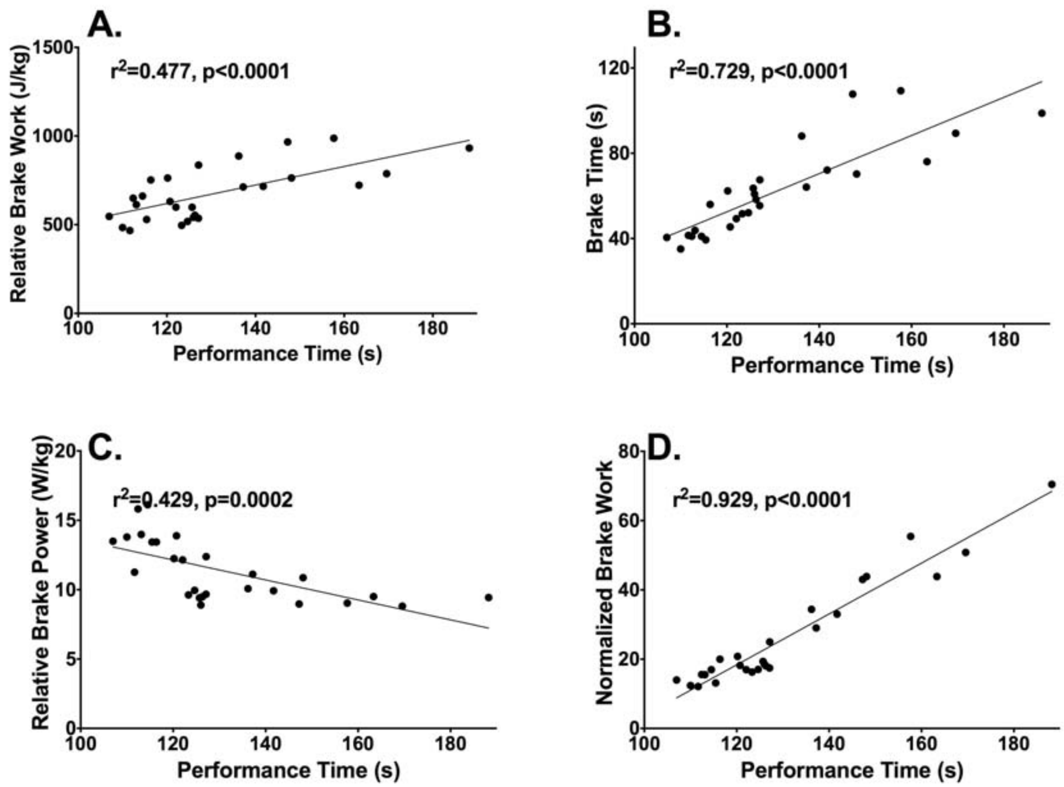


Figure 9.2. The relationship between Performance Time (s) on the mountain bike descent and A) relative brake work (J/kg); B) brake time (s); C) relative brake power (W/kg); and D) normalized brake work.

Based on overall performance time, one trial was selected each from a high-performer (performance time= 115.4 s; normalized brake work= 13.1; relative brake work= 529.1 J/kg) while another was selected as that of a low-performer (performance time= 169.9 s; normalized brake work= 43.0; relative brake work= 966.5 J/kg). The relative brake power and normalized brake power from a small section of these trials are highlighted in Figure 9.3, which was chosen due to clear visual differences for each of comparison. From each entire trial, a histogram was created to indicate the magnitude of normalized brake power as a percent of brake time (Figure 9.4). Normalized brake power was organized into 10 bins which were separated by 0.05 1/s. Values below 0.05 1/s were removed from analysis since these were extremely light braking events, while values above 0.5 1/s were all included in the same bin due to their minimal occurrences.

9.2 Discussion and Implications

Braking has been identified as an important factor for performance in mountain biking; however, the kinetic energy of the bicycle-rider system—and thus the brake work required to slow the system—is proportional to the mass times velocity squared of the system, which complicates traditional metrics. This is the first investigation to utilize an algorithm to normalize brake power as a proportion of the kinetic energy of the bicycle-rider system, effectively scaling rider input to the brakes to both mass and velocity. It was hypothesized that normalized brake work would be more strongly associated with descending performance than traditional brake power meter metrics. Although relative brake work, brake time and relative brake power were all significantly associated with performance time on a mountain bike descending track (Figure 9.4A-C), normalized brake work explained more variance in descending performance time on the track used in this study (Figure 9.4D).

Eq. 9.1-3 highlighted some of the complexities when utilizing traditional brake metrics such as relative brake work and relative brake power to explain variations in XCO-MTB descending time. The present method for calculating normalized brake power (Eq. 9.4) normalizes instantaneous brake power based on mass and velocity, and is indicative of the proportion of kinetic energy removed at any time during braking. Once this is integrated over time (Eq. 9.5), the resultant normalized brake work metric theoretically offers a broader representation of the conservation of kinetic energy with respect to braking than traditional brake measures. Since the potential energy of the bicycle-rider system is a product of the mass of the system times the height of the track and gravity, and there was negligible propulsive work completed by participants, the normalized brake work algorithm has sound theory for use in explaining the present descending performances.

The results presented in this study firstly reinforce the relationship between braking and mountain bike descending performance (Figure 9.2A-C). Indeed, the fastest performance times were associated with reduced relative brake work, reduced brake time, and increased relative brake power. These findings are not surprising, but support the qualitative importance of efficiently controlling the speed of the bicycle down the hill (Chidley *et al*, 2014; Hurst & Atkins, 2006) and reinforce earlier braking investigations (**Chapter 6**; **Chapter 7**). However, the main finding presently is that the normalized brake work metric was more strongly related to performance (Figure 9.2D), and can therefore explain more variation in descending performance than traditional measures from a brake power meter. This finding is promising because normalized brake work can indeed explain the variation in descending performance based on brake power meter data alone, thus eliminating the need for qualitative measures of descending performance or for other equipment. Moreover, the single metric output reduces the complexity of multivariate analyses of braking performance, which eliminates a potential barrier to use of the brake power meter.

It is perhaps surprising that the relationship noted presently is nearly the same strength as the previous multivariate model (r^2=0.935; **Chapter 6**), however the normalized brake work algorithm assesses descending performance solely. This is a strength in its own right because it is well known that propulsive power can explain ascending performance. Just as earlier investigations helped to understand that ascending performance can benefit from increased propulsive power (Gregory *et al*. 2007), XCO-MTB athletes looking to increase descending performance can look to reduce normalized brake work. Future research might look at assessing performance during propulsive segments of mountain biking (e.g. ascents) based on propulsive power, and non-propulsive performance (e.g. descents) based on the present model, which may provide better clarity on overall performance.

Given the validity of normalized brake work as a descriptor of descending performance, it is important to look to training inventions that can help to reduce this value. Therefore, two visual examples of normalized brake power are highlighted in Figure 9.3 and 9.4. By inspection of Figure 9.3, it can be seen that the normalized brake power graph helps the reader to visualize the proportion of kinetic energy being removed during each braking event by each rider. It is clear in this figure that the low-performer is completing greater normalized brake work, which is mainly due to braking across a greater distance. Figure 9.4 helps to indicate the proportion of braking done within the spectrum of normalized brake power. The high-performing rider spends a greater proportion of brake time conserving a greater amount of kinetic energy, whereas the low-performing rider spends a greater proportion of brake time removing high amount of kinetic energy. Thus, the low-performer could be able to perform better by reducing time spent removing large amounts of kinetic energy. Ultimately, these are examples of the observations that may help indicate changes that can be made through brake training interventions and are in addition to the broad representation of descending performance based on normalized brake work.

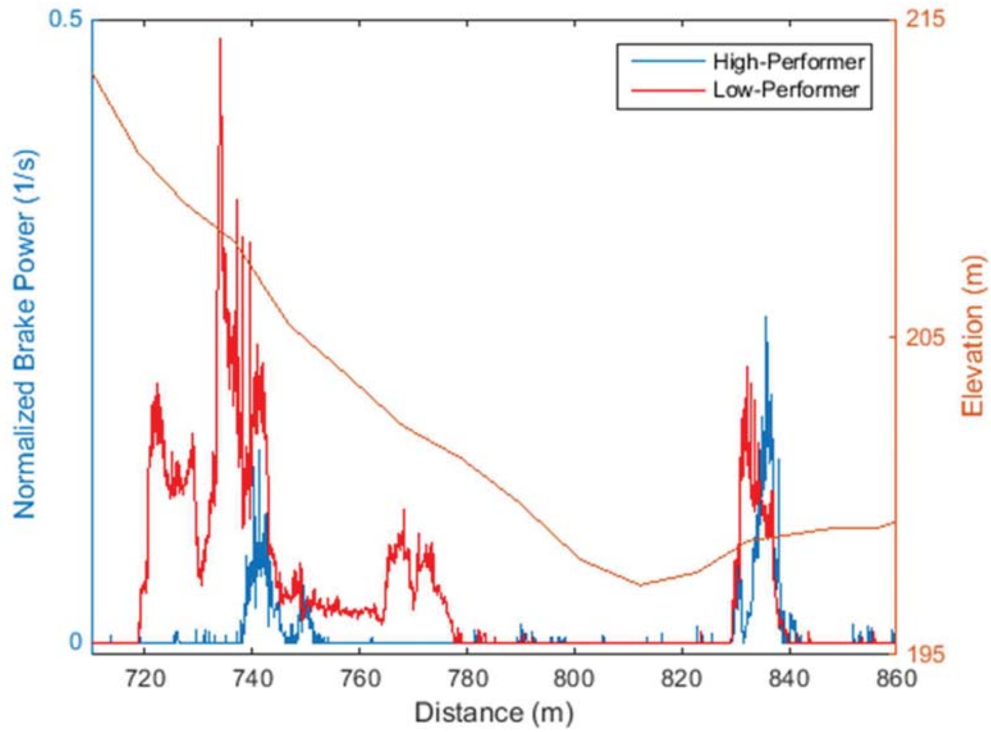


Figure 9.3. Graphical representation of normalized brake power (1/s) across a 150 m portion of the descent from one trial each by a high-performing and low-performing mountain biker. The normalized brake work was 0.13 and 0.80 for the high-performer and low-performer, respectively. The time to complete this section was 14.72 and 18.22 s for the high- and low-performer, respectively, which equated to 10.91 and 8.23 m/s, respectively.

Presently, the normalized brake work algorithm is not a perfect model, and the remainder of the variation in performance is attributable to a number of extraneous braking variables. One factor affecting performance is the location of the braking, which has been previously been identified as a major difference between experienced and inexperienced riders (**Chapter 7**). This is a factor that could likely benefit from visual inspection and should be explored further. Another braking factor affecting descending performance in the shape of the braking curve, as can be seen in Figure 9.3. A late-braking strategy is displayed by the high-performing rider, and acts to reduce performance time since a greater proportion of the time is spent moving more quickly. While the shape of the braking curve may indeed affect performance, this is a small difference that cannot be understood solely by looking at normalized brake work and may likely rely on visual inspection. Similarly, line choice likely factors in to performance differences as well. Firstly, these could be analysed based on GPS position, though these devices lack some resolution (Coutts *et al*. 2010). However, it may be possible to use helmet camera video footage analysis, which would give a better indication of location along the trail and also the path taken.

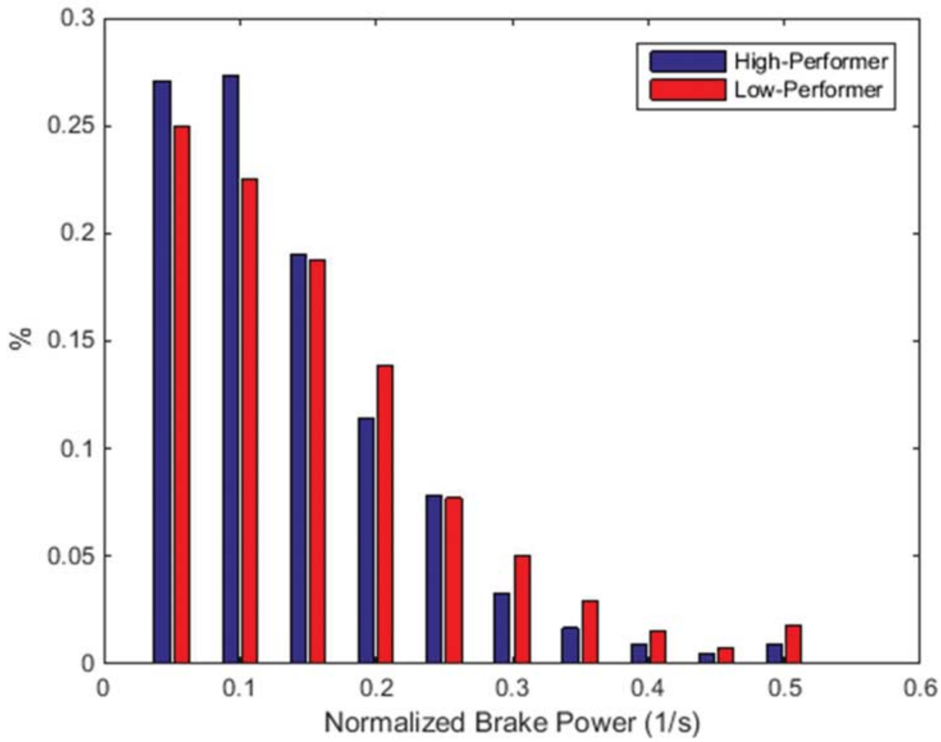


Figure 9.4. Frequency distribution of normalized brake power (1/s) comparing a high- and low-performing mountain biker. Normalized brake power was separated in to 10 bins in 0.05 1/s steps, with values below 0.05 1/s removed from analysis and values above 0.5 1/s combined in the same bin.

9.3 Conclusion

This study shows that the normalized brake work algorithm has sound theoretical reasoning for use in comparing brake data between riders going different speeds. Normalized brake work can describe more variation in descending performance than other braking measures, which gives the brake power meter greater utility as a training tool. It is recommended that training interventions be utilized to enhance the braking patterns of low-performing mountain bikers, which should come as a benefit to their normalized brake work.

Chapter 10

DISCUSSION

10.1 General discussion

This body of work originally sought to better understand the physiological demands XCO-MTB descending. While these descending sections within XCO-MTB competitions are not always decisive, a deeper understanding of these was clearly important due to the demanding nature of the terrain. Thus, **Chapter 4** furthered on from previous work by Macdermid *et al* (2017), and added new knowledge by investigating physiological and vibrational differences between descending road and off-road surfaces. **Chapter 4** also investigated the differences in a coasting versus pedaling strategy on a descent—this ended up being a turning point for the direction of this research. When it was uncovered that riders were able to descend at the same pace whether coasting or pedaling, it became clear that this needed to be investigated more closely. The determination was made that a method to measure descending ability needed developing, and the brake power was the measurement method that this body of work focused on.

Brake power was chosen as the measurement to investigate firstly due to its acceptance in the cycling world. Cyclists and practitioners have been groomed to understand the basics of propulsive power, which gave brake power strong face validity. Power was chosen in lieu of a measurement such torque due to its usefulness for calculating energy losses (e.g. brake work).

With that, the novel brake power meter described in **Chapter 5** was developed. By calculating the energy losses during braking and comparing them to other equations of energy, the device was able to be validated within the same chapter. This thesis is not towards an engineering degree, and therefore Chapter 4 is not intended to be written as an engineering manuscript. **Chapter 5** does however fully explain how the device works and how the device was validated, which is the main point for application in the sports science area. As such, this Chapter does not address the time or methodology set aside to design the brake power meter, nor does it speak too in-depth on how it works (e.g. software, hardware, etc.) besides practically. This chapter as presented is the product of the varied feedback received throughout an intense peer review process. It was no easy feat to gain acceptance of this manuscript, however this stands as testament to the study's rigor.

From this point, it was important then to determine what a brake power trace might look like during mountain biking, which was the focus of **Chapter 6**. It came as no surprise that braking was related to XCO-MTB performance, though this finding was important to communicate within the scientific community. Another important finding of this study highlighted that it is possible to offset performance decrements due to fatigue simply by braking differently. A promising inference from that finding was that it may be possible to enhance performance by braking differently. It was that inference that led to the testing protocol used in **Chapter 7**. Henceforth, clear differences in braking and performance were noted between inexperienced and experienced mountain bikers. These differences were important to note, and it is the hope that one day coaches can use this information to train riders to brake more efficiently. It was not within the scope of this thesis to investigate brake training strategies, mainly due to the need to focus on quantifying other aspects of braking.

One small aspect of braking that required investigation was a method to quantify brake power during skidding. **Chapter 8** describes this method well, and offers a sound, valid solution to brake power calculation in a non-moving wheel. Due to the time course of this body of work, it was not seen as practical to go back and recalculate data from **Chapter 5-6**. While this might be considered a limitation of this thesis, the reader is reminded that the time spent skidding during XCO-MTB is minimal, as pointed out in **Chapter 5.**

The final experimental chapter of this thesis aimed at determining practical, easy method for assessing descending performance based on braking. It is one thing for a sports scientist to describe differences in brake power, brake work and brake time between individuals, and a totally different thing for a mountain bike enthusiast to quickly compare himself to his friends after a fun ride. The scientific method was utilized to explore the single metric output and is described in-depth in **Chapter 9**. The hope is that this finding will make brake power meter data less intimidating and more useful for the hopeful day that the brake power meter is available for consumers.

10.2 Practical applications

Overall this body of work highlights the need and importance of the brake power meter in XCO-MTB performance analytics. This is made clear from the conclusion of **Chapter 4** when it was discovered that riders could descend at the same pace whether coasting or pedaling, and was reinforced in each subsequent experimental chapter. It is perhaps not surprising that braking is so strongly associated with things like descending performance, however it is important to note that—to the Candidate's knowledge—this is the first time that any aspect of braking during cycling has been explored. The authors believe that they are not the first to have thought about the importance of braking for mountain biking, and indeed other scientific authors have been hinting at something like this for several years (Mastroianni *et al.* 2000; Macdermid *et al.* 2016). But, what the authors do believe is that exploring the measurement of braking was a right-place-at-the-right-time kind of situation; indeed, there was one researcher available (in this case, the Candidate) to dedicate several years of research in to developing and employing a brake measuring device through sounds scientific research.

After the completion of **Chapter 4** and the initial development of the first prototype, there were a number of outstanding downhill mountain bike events in which racers rode very well with no chain. While many racers would have given up and accepted a poor performance, there were a number of athletes who used a broken chain mishap to their advantage. Of note was Aaron Gwin's (2016 Overall World Cup Winner) World Cup race win in Leogang, Austria in 2015, a race in which he was the fastest competitor despite breaking his chain at the start of the race. While this came as a surprise to many within the sport, it came as no surprise to the researchers within this project. Though this research program never really did get to the bottom of how riders are able to ride downhill on select tracks whether coasting or pedaling, the data presented throughout this thesis tend to support the reasons this might be possible. Perhaps there is an increased ability to concentrate on technique when the effort is low? It is the Candidate's hope that one day this might be investigated.

One thing that has been interesting since the onset of this research program has been the increasing use of brake measurement tools in professional mountain bike racing. Of note are a number of teams using test-only bikes, which are not dissimilar to the test bike used in the present investigations. These feature an on-board data logger and proprietary brake sensors—usually pressure sensors within the brake line. It seems that brake pressure sensors are utilized because they are more compact, and thus lighter; however, the authors in the present investigations decided against the measurement of brake pressure since the effectiveness of brake pressure at slowing down the rotation of the wheels is dependent on the heat of the braking equipment at any time. What this means is that for a given brake pressure, the effect on slowing the bike is not always the same, which reduces the robustness of measurements. While this issue is resolved by measuring brake power, to date it has been difficult to build lightweight brake power measuring devices; indeed, the present device adds 5 kg to the weight of the bike. The weight of equipment (and cyclist, for that matter) is a concern within racing, and it has been noted that while data loggers and brake pressure sensors might be lightweight enough to add to a bike for training or testing, these units are not lightweight enough to race on (~1-2 kg additional weight for data logger and pressure sensors). As a result, any data that has since been collected—whether within this thesis or by professional racers—has not been from actual race performances.

Given the importance of braking noted throughout this thesis and the lack of proper tools available, the Candidate was determined to bring a brake power meter to the market. This led to a number of successful funding applications aimed at miniaturizing and commercializing a bicycle brake power meter. At the time of writing this thesis, a bicycle brake power meter has successfully been developed through our original intellectual property with a technology partner in Denmark. It is the Candidate's hope that this smaller device—and the research completed herein—will encourage riders to look deeper in to their braking habits to create for themselves informed braking decisions for a safer and faster ride.

Figure 10.1 The Candidate with an early commercially viable prototype brake power meter. Photo c. David Wiltshire, Massey University.

With this in mind, it has always been a goal to collect robust, useful data. At the onset, the data have been displayed as in practitioner software, such as in Figure 5.4. It was clear that by using controlled trails such as the isolated turn in **Chapter 7**, the data were easy to compare. For example, by controlling the line taken (by way of a narrow track), and by starting at the top of the track in the same manner (coasting with no chain), the distance ridden and resulting brake power trace were easily comparable. However, the utility of these small differences were harder to notice once the brake power meter was taken out and used more casually. For example, we tried taking beginner mountain bike riders out and training them based on their braking patterns, by looking at data traces as in Figure 5.4. However, the implications of braking weren't clear to the rider until after several sessions using the brake power meter. To alleviate this, we tried attaching a video camera to the helmet of the rider, and using time-series adjustments post hoc to align the rider's view of the trail with the braking that had been completed (Figure 10.2). This proved useful to both the rider and the practitioner, and after a few sessions the rider was able to ride the track more quickly. An interesting outcome of review of the helmet camera data was that it became apparent what other skills the rider could work on, which was based on some of the locations of excessive braking across the trail. For example, one particular rider was completing a lot of brake work preceding the jumps on the track. This braking was due to the rider not being confident on jumps. As such, it was determined that the rider could focus on practicing jumps, with the hope that this excess braking could eventually be eliminated.

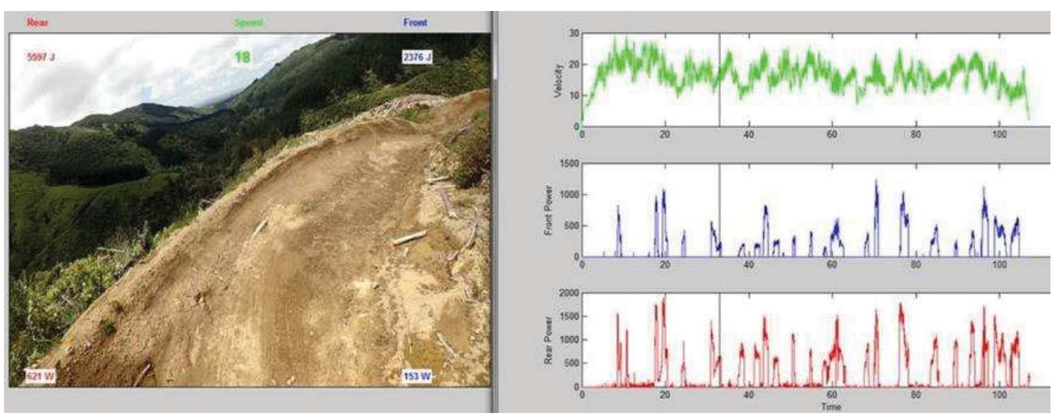


Figure 10.2 An example of helmet video recording of the rider's view of the trail and the braking trace completed throughout the trial.

The kind of findings communicated in regards to the helmet camera are recent findings, and are not meant to be communicated scientifically; indeed, the scientific method was not utilised to collect these data. These highly practical data were difficult to collect [at first], but the utility is clear—it shouldn't take a PhD to figure out what some brake power readings displayed on a helmet camera might mean. At the same time, the highly practical description of the data is the most important part: brake power meter data *should* be easy to collect, easy to analyse, and easy to do something about it. These are the types of attributes that make scientific findings useful in sport! The Candidate would lament that this helmet camera finding is also one of the most important findings of this thesis, which is thanks to its highly relatable nature. Of course, the findings garnered scientifically were important: hypotheses were based on previous findings, which reduces the need for data mining and witch-hunts; there was rigour to the methodology, which means that the protocol are repeatable; statistics were employed to guide the utility of the findings; etc. This allows the obscure audience of readers of this thesis and the refereed publications to have confidence in the application of what is communicated presently, which is of course the whole point of the scientific method. However, this was an extremely long, drawn out process, during which a lot of time was spent doing curiously tedious and regal tasks simply to check administrative boxes. Sadly, this is not the pace of the real world; the real world moves much more quickly than the two years it takes to bring novel findings from the editor to the people. Sadly, in this time the industry is still moving and looking for the next product to put in front of the people (note: this is to the benefit of both the company and the people, as it were, in this case). Sadly, oftentimes science is left in the dust, and we are stuck making corrections on our third review of old data.

It is the Candidate's hope that the data collected scientifically is now completed, and that time will pass much more quickly between the first brake power meter being made available to the first athlete being coached with a brake power meter. Ultimately this would signal a successful foray into applicable sports research.

10.3 Thesis limitations

This thesis offers a glimpse in to the importance of braking during XCO-MTB; however, there are a number of limitations to the findings, but especially to the utility of the present data. Individual limitations are discussed in each chapter, and this helps the reader to understand minor limitations throughout the thesis. However, there are a number of concerns never addressed; these are addressed below.

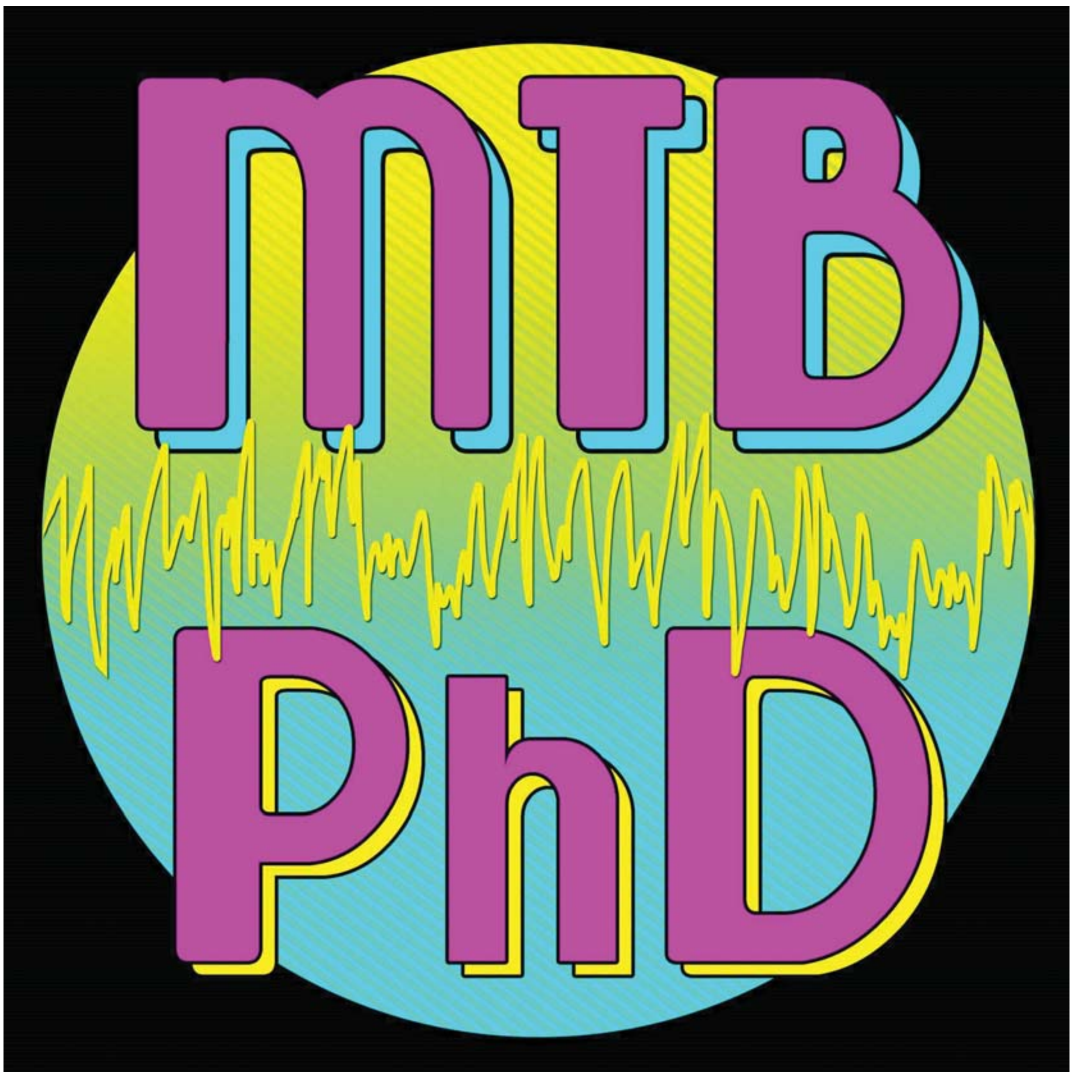
One of the first issues that may come up depending on the reader is the variables measured herein using the brake power meter. Namely, some might find issue in the fact that we measured brake power. As argued previously, the researchers felt that power was an appropriate measurement to explore since it is easily converted to energy, and power/work/energy measurements had already become well-accepted in cycling (this is reinforced in **Appendix I**). However, much deliberation has remained. Some have suggested that measurements collected with the brake power meter could have stopped at torque, from which acceleration (m/s/s) can easily be calculated. The argument against measuring torque stands on the basis that torque measurement itself does not give an indication of the work done/energy removed from the bicycle-rider system through braking. Similarly, there could be a measurable brake torque when the bike is not moving; for example, imagine a cyclist pointing down a hill with his brakes on, but not moving—in this case there would be a brake torque, but it is not slowing the cyclist down nor is it something that is affecting the extent to which he is riding since he is not actually moving. In that regard, there could be a high torque or a very high torque, but neither one is slowing him down more than the other. This in itself might render the measurement of only torque less useful for training purposes.

Another limitation to the present collection of research is that none of these manuscripts are training manuals. At that, it is important to note that none of this research has explored the trainability of braking to improve performance. This is perhaps in reverse to such data as that garnered from propulsive power meters, since it had already been well-established that training could increase propulsive power in the laboratory. This meant that appropriate training strategies had already been established before personal power meters made their way to the market. As it stands currently, clear differences have been shown between experienced and inexperienced mountain bikers (**Chapter 7**), and it is clear that changing braking can result in faster speeds (**Chapter 6**). However, to date there is no clear training path to improve braking strategies. It is recommended that appropriate brake training strategies be explored, both in the field and within the science community.

Another limitation is to the algorithm used to calculate normalized brake power in **Chapter 9**. It should be pointed out that this is not a standard calculation, and the ratio of brake power to kinetic energy does not actually result in a number that is a power (e.g. rate of work). Rather, since this is a rate of work taken as a proportion to an energy, the units are 1/s. However, it should also be pointed out that by using the calculation explained, brake power is indeed displayed as a ratio of kinetic energy, which makes the name 'normalized brake power' more intuitive. Moreover, once this is integrated to calculate normalized brake work (appropriately unitless), the coefficient of determination explained within **Chapter 9** indicates the strength of the equation used. Thus, it is suggested that normalized brake power is suitable for use to make brake data easier to view according to one metric, however this could likely be called by another name.

10.4 Conclusions

Descending on a mountain bike is physiologically demanding, and strategies should be taken that can reduce the physiological demand during these sections. The use of a brake power meter offers greater insights in to mountain bike descending performance, and it is recommended that training strategies be explored to enhance riders' braking strategies.



Appendices

This portion of the thesis includes an additional manuscript that was written and published (Appendix I).

Appendix I

Agreement between the Powertap, Quarq, and Stages power meters for cross-country mountain biking.

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Abstract

Advances in technology have made the use of a variety of power meters ubiquitous in road cycling along with an ever-increasing popularity during mountain biking. This study compared data from one bicycle using three power meters: Stages (non-drive-side crank arm); Quarq (chainring spider); and Powertap (rear wheel hub). While no differences ($P>0.05$) between power meters were present during treadmill riding at high or low cadences, dissimilarities for both power (W) and cadence (rpm) were apparent during actual cross country mountain bike riding. Frequency distribution and analysis of coasting indicate that the Stages records more time ($P<0.001$) at zero watts (6.9 ± 3.3 s) and zero cadence (6.9 ± 3.3 s) compared with Quarq (W= 3.3 ± 1.5 s, rpm= 0.8 ± 0.7 s) and Powertap (W= 1.1 ± 0.8 s, rpm= 3.0 ± 1.2 s). Consequently, significant interactions (power meter*terrain, $p=0.0351$) and main effects (power meter $P<0.0001$, and terrain $P<0.0001$) for power output were present and included: uphill (317.5 ± 50.7, 340.8 ± 52.6, 327.3 ± 48.6 W); downhill (127.6 ± 12.3, 147.4 ± 23.8, 160.1 ± 24.0 W); and flat (201.1 ± 21.6, 225.2 ± 27.2, 224.0 ± 29.6W) for the Stages, Quarq and Powertap, respectively. It is likely that accelerometry (Stages) compared with reed switch (Powertap and Quarq) technology to determine cadence, resulted in the discrepancies between power meters. However, while the reliability of the different methods appears acceptable for intermittent exercise such as cross-country mountain biking, the validity of each in such a situation requires confirming.

Keywords: mountain bike; power meter; cycling; cross country; power

Introduction

The use of power meters has become ubiquitous to observe competitive work requirements and also to monitor training load in serious cyclists (Jobson, Passfield, Atkinson, Barton, & Scarf, 2009; Pinot & Grappe, 2011). Historically reserved for use in only elite sport and at a high cost, advances in technology have made these devices readily available at relatively low cost. Most power meters use strain gauges to measure strain-inferred torque and utilize various methods to measure pedal cadence (Aguilar, 2008). These values are continuously sampled, multiplied and typically reduced to 1 s averages, with power displayed in real time on portable display units. The data can be downloaded onto a personal computer for review and analysis of training and racing data. While power is a relatively simple and universal measurement, power meter manufacturers have taken different approaches in the way equipment works, each with potential benefits (e.g. reduced weight penalty or overall cost) or shortcomings (e.g. indirect measurements). For example, the Powertap (Saris Cycling, Madison, WI, USA) houses strain gauges in the rear hub and estimates cadence through wheel speed. The Quarq (Quarq, Spearfish, SD, USA) uses strain gauges in the crank's chainring spider to measure strain and a magnet fixed to the bicycle for cadence measurement. Others, like the Stages (Stages Power, Boulder, CO, USA) use a strain gauge housed in only the left crank arm to measure power with an attached accelerometer to measure cadence.

Many cycling studies have used the SRM power meter for research (Johnson, Stannard, Chapman, & Thompson, 2006; Johnson et al., 2003; P. Macdermid & Edwards, 2010;

Pinot & Grappe, 2011; Smith, Davison, Balmer, & Bird, 2001) as this device has been shown to be a valid means of reflecting power (Martin, Milliken, Cobb, McFadden, & Coggan, 1998). However, frequency of use should not confer "gold standard" status inferred to the SRM as a cycling power measuring device; even the 'Professional' model with four strain gauges has a claimed ± 2% accuracy (Gardner et al., 2004). The error associated with the Powertap is ± 2.5 % and this device has been deemed acceptable for use in training and in road cycling following direct comparisons with the SRM (Bertucci, Duc, Villerius, Pernin, & Grappe, 2005; Gardner et al., 2004). The claimed error associated with the Quarq power meter is ± 2 % (Aguilar, 2008; P. W. Macdermid, P. W. Fink, & S. R. Stannard, 2014), which is the same as for the power associated with the left leg in the Stages power meter according to manufacturer's claims.

There currently exists no comparison of the Quarq power meter with other acceptable devices like the Powertap as has been done previously with other new devices (Abbiss, Quod, Levin, Martin, & Laursen, 2009; Millet, Tronche, Fuster, Bentley, & Candau, 2003; Sparks, Dove, Bridge, Midgely, & McNaughton, 2015). Researchers should be concerned by the assumptions made with the Stages power meter in particular, whereby torque produced by the left leg is measured and assumed identical to that of the right leg. In this context, power asymmetries are commonly seen between dominant and non-dominant legs (Meylan, Nosaka, Green, & Cronin, 2010), which could introduce a source of error in power measurement. This power meter has been reviewed once for off-road climbing, however little attention was paid to the fact that this device also assesses cadence differently and through the use of an accelerometer (Hurst, Atkins, Sinclair, & Metcalfe, 2015).

In addition to fundamental differences in the way these devices work, no studies to date have assessed the agreement of different power meters for variable-terrain cross-country mountain biking (XCO-MTB), with investigations exclusively reviewing power meters for use in either road or laboratory cycling, even though studies on this particular discipline of the sport have used various power meters (Hurst & Atkins, 2006; P. W. Macdermid et al., 2014; P. W. Macdermid & Stannard, 2012; Miller, Moir, & Stannard, 2014; Stapelfeldt, Schwirtz, Schumacher, & Hillebrecht, 2004). XCO-MTB off-road terrain produces more intermittent demands with a higher proportion of time producing either no power while coasting, descending, or through corners, and alternately interspersed with supramaximal bursts of pedalling (P. W. Macdermid & Stannard, 2012; Miller et al., 2014; Prins, Terblanche, & Myburgh, 2007; Stapelfeldt et al., 2004) when compared with road cycling. Cadence has also been shown to be different during XCO-MTB than in road cycling, with more time spent producing power though high-force low-velocity pedalling than on the road (P. W. Macdermid & Stannard, 2012). The unique demands of XCO-MTB collectively suggest it could present some of the more difficult challenges to measuring power during cycling, especially if work in only one leg is recorded. As power meters have been used to assess the slight differences that equipment can have on performance in the field (P. W. Macdermid et al., 2014; MacRae, Hise, & Allen, 2000), determine pacing (Skiba, Clarke, Vanhatalo, & Jones, 2014), and concurrently to track training and measure fitness (Miller et al., 2014; Prins et al., 2007), it is important that power meters be able to instantaneously and accurately reflect power, regardless of the type of equipment used or terrain ridden. Moreover, some of these devices function by relatively novel means (e.g. Stages), so it is important that these be compared to equipment currently considered acceptable.

The purpose of this study therefore is to compare the recordings of power produced by the Powertap, Quarq and Stages power meters simultaneously on one bicycle. As fundamental differences in ability to measure steady-state power could drastically affect any intermittent measurements in the field, this study first set about to compare power under a controlled laboratory environment during steady cycling. The primary aim of this study was to assess the agreement between power meters during a simulated XCO-MTB time trial completed on varied off-road terrain. It is hypothesized that the equipment will provide agreeable readings of both power and cadence throughout laboratory and field trials given manufacturer's claims and despite utilizing different technology to measure power or cadence.

Methods

Laboratory and Field Equipment

A mountain bike (GT Zaskar, Force Carbon Construction) was built for use with three different power meters simultaneously. A Stages Power SRAM X9 power meter (Stages Cycling, Boulder, CO, USA) replaced the left crank arm while a Quarq Quatro (Quarq, Spearfish, SD, USA) replaced the right crank. The rear wheel was replaced with a Powertap Pro MTB rear hub laced to a Stan's ZTR Olympic rim. The magnet used to read cadence for the Quarq power meter was placed at the 6 o'clock position around the frame's bottom bracket shell, while no changes were made to the Stages or Powertap to enable external cadence measurement. Tire pressure was standardized at 0.3 PSI/kg of body mass (Paul William Macdermid, Philip W. Fink, & Stephen R. Stannard, 2014). Participants used their own pedals and shoes and positioned the saddle position to personal preferences. Each power meter was synchronised with a reliable, independent, commercially available portable headunit (Garmin, Edge 510, Olathe, KS, USA) (P. W. Macdermid & Stannard, 2012). Data were logged every second based on the maximum recording rate of the headunit. Trials were distinguished by pressing the 'LAP' button simultaneously by two technicians to eliminate differences in recording time at the beginning and end of each trial. All participants provided a signed informed consent for the protocols that were approved by the institution's human ethics committee.

Study A

Four nationally competitive cyclists (64.3 ± 10.5 kg) volunteered for the laboratory study which involved riding on a treadmill at 20 km/hour at a + 6 % gradient. Participants cycled in two different rear cogs (either 12 or 18 tooth rear cog) chosen to elicit a low or high cadence, respectively, for 10 min in a random order. Recording of data did not commence until the participants were riding at a steady cadence and concluded before the treadmill speed was reduced. Participants were allowed 15 min epoch between trials.

Study B

Eight nationally competitive XCO-MTB athletes (61.0 ± 2.6 kg) volunteered for the field trials that were completed over one lap of a 1.67 km purpose-built off-road track (Arapuke Forest, Palmerston North, New Zealand) of which all participants were familiar. Following a 30 min warm-up and re-familiarization with the track, participants were encouraged to complete the trial at race pace. Data were logged simultaneously as per *Study A*.

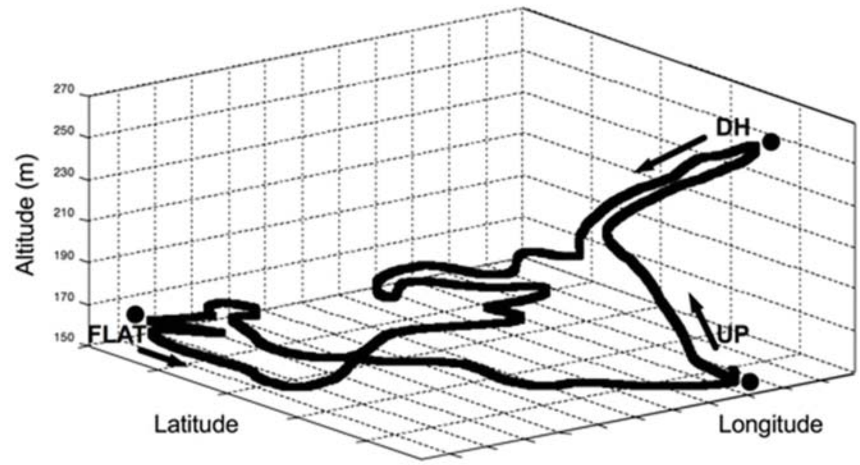

Figure 1. XCO-MTB lap with UP, DH, and FLAT sections indicated.

The track (Figure 1) was broken down into three sections according to overwhelming terrain trend and deemed as uphill (UP), downhill (DH) and flat (FLAT) with distances of 348, 763, and 559 m, respectively, and elevation change of 15, -22, and 10 m, respectively. The UP section took place on a forest road, while the DH and FLAT sections were groomed rolling singletrack terrain in dry condition. Data were continuously sampled and logged every second and transferred to Garmin Training Center (version 3.6.5) on a conventional PC for analysis.

Statistical analyses

Descriptive data (mean, standard deviation and coefficient of variation where appropriate) were calculated for power and cadence during treadmill riding in each cadence condition and during the XCO-MTB lap by terrain section. Two-way repeated-measures analysis of variance (ANOVA) was used to compare power within each cadence condition during treadmill riding (power meter*cadence), and to compare power and cadence measured off-road by terrain section (power meter*terrain). One-way repeated-measures ANOVA was used to analyse coasting duration (seconds) for power or cadence recorded.

Where significant difference was found the main effect was analysed using Tukey post-hoc testing. All statistical analyses were performed using GraphPad Prism 6, significance set at $P<0.05$.

Power and cadence for each terrain section were broken into 50 W and 10 rpm bins for frequency distribution and displayed as relative frequency. The first instance of coasting during the transition from the forest road (UP) section to the singletrack (DH) was analysed for duration (s) of values recorded as 0 W and rpm for each power meter (Figure 6) to determine possible source for differences in recorded mean values and frequency of measurement

Results

Study A

For treadmill riding, mean power (± CV %) was 225.6 (± 1.77%), 220.0 (± 2.47%), and 221.5 (± 3.11%) during the low cadence trial, and 233.5 (± 2.45%), 217.5 (± 2.70%), 223.1 (± 2.09%) during the high cadence trial for the Stages, Quarq and Powertap power meters, respectively. Two-way ANOVA indicated no interaction (power meter*cadence, $F_{(2,12)}=0.9170$, $P = 0.4260$) in the low or high cadence conditions, or significant main effect for cadence ($F_{(1,6)}=0.0135$, $P = 0.9112$) thus highlighting robustness for power measurement in the two cadence ranges within each power meter. However, there was a significant main effect for power meter ($F_{(2,12)}=4.036$, $P = 0.0457$) indicating differences in equipment used. Post-hoc testing indicated no significant differences ($P>0.05$) between power meters during steady riding. Mean cadence within each condition was not significantly different ($P>0.05$) with the mean ± SD rpm equalling 59.4 ± 0.5 , 59.2 ± 0.3, and 58.8 ± 0.2, during the low cadence trial, and 88.9 ± 0.6, 88.6 ± 0.6 and 88.6 ± 0.6 during the high cadence trail for the Stages, Quarq and Powertap, respectively.

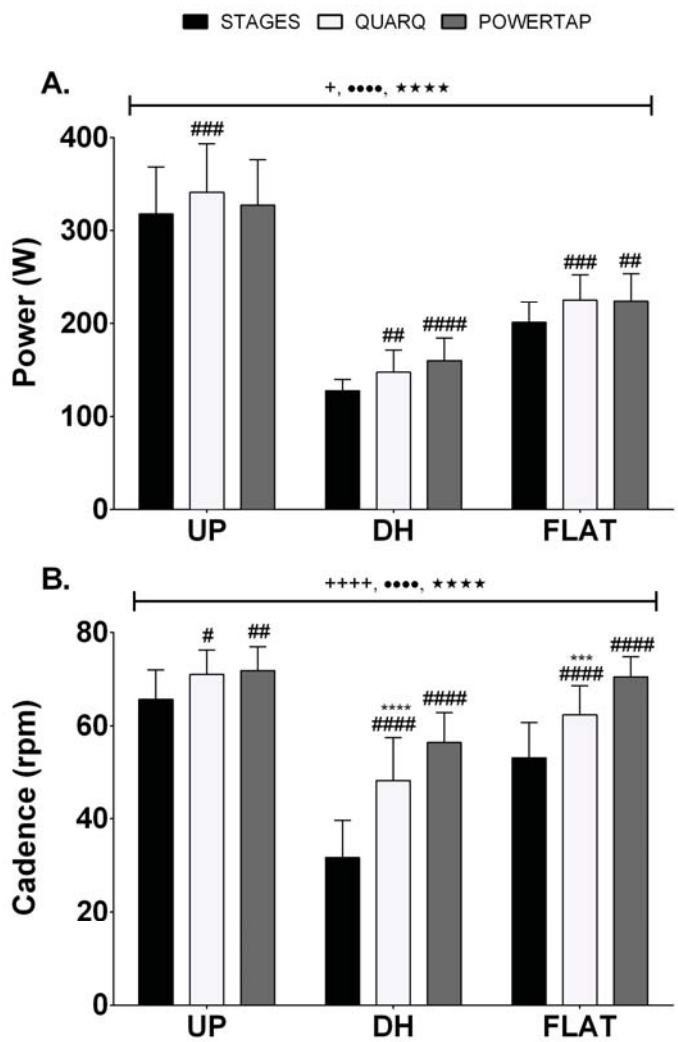

Figure 2. Mean (± SD) A. power (W) and B. cadence (rpm) in terrain section during XCO-MTB lap.

+ (P<0.05), ++++ (P<0.0001) interaction between power meter*terrain; •••• (P<0.0001) main effect of power meter; ★★★★ (P<0.0001) main effect of terrain. Post hoc analysis *** (P<0.001), **** (P<0.0001) when compared to Powertap; # (P<0.05), ## (P<0.01), ### (P<0.001), #### (P<0.0001) when compared to Stages.

Study B

Analysis of power (Figure 2A) provided a significant main effect for power meter ($F_{(2,42)}$=27.1600, P <0.0001) and terrain ($F_{(2,21)}$=60.2712, P<0.0001), with a significant interaction for terrain*power meter ($F_{(4,42)}$=2.8558, P =0.0351). Post-hoc analysis revealed significant difference between the Stages and Quarq for UP (P<0.001) as well as between the Stages and both Quarq and Powertap (P<0.01) in the DH and FLAT terrain sections.

Analysis of cadence (Figure 2B) showed a significant main effect for power meter ($F_{(2,42)}$=129.236, P <0.0001) and terrain ($F_{(2,21)}$=33.8695, P <0.0001) and a significant interaction for terrain*power meter ($F_{(4,42)}$=14.9330, P <0.0001). Post-hoc analysis identified that the Stages was significantly different (P<0.05) in all sections compared with Quarq and Powertap, and that the Quarq and Powertap were significantly different (P<0.001) from each other in the DH and FLAT.

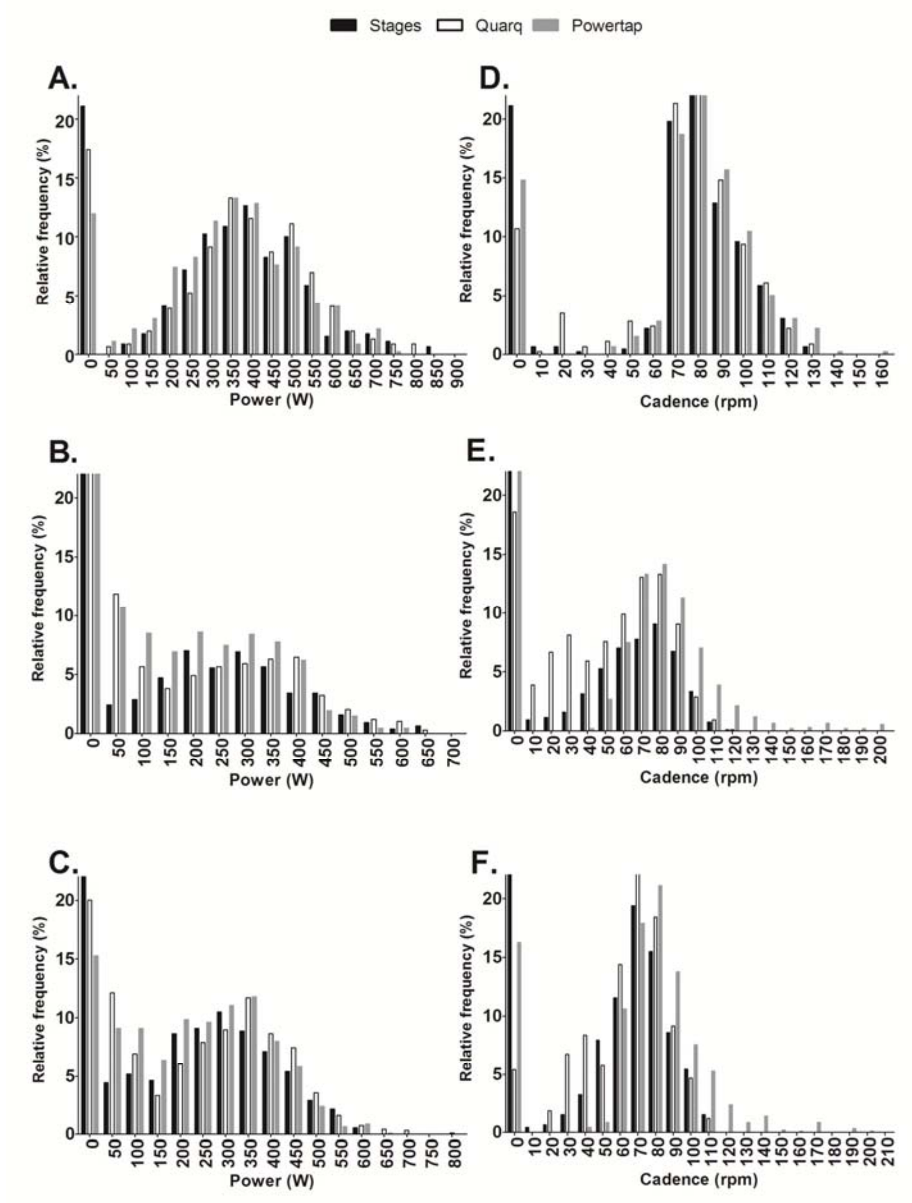

Figure 3. Frequency distribution for power (A, B, C) and cadence (D, E, F) across terrains displayed as relative frequency for each power meter. A, D: UP; B, E: DH; and C, F: FLAT.

Frequency distribution (Figure 3) highlights disagreement in recorded values amongst power meters as well as a difference per terrain section. One-Way ANOVA of coasting duration showed mean duration of 0 power (Quarq= 3.3 ± 1.5 s, Stages= 6.9 ± 3.3 s, Powertap= 1.1 ± 0.8 s) was significantly different between the Stages and Quarq ($P<0.01$) and Stages and Powertap ($P<0.001$), but not significantly different between the Quarq and Powertap ($P>0.05$). Mean duration of 0 cadence (Quarq= 0.8 ± 0.7 s, Stages= 6.9 ± 3.3 s, Powertap= 3.0 ± 1.2 s) was significantly different between the Stages and Quarq ($P<0.001$) and Stages and Powertap ($P<0.01$), but not significantly different between the Quarq and Powertap ($P>0.05$). Recorded power and cadence coasting duration were significantly correlated in the Quarq and Powertap ($r = 0.7467$ and $r= 0.7161$; $P= 0.0333$ and $P=0.0457$, respectively), and a perfect fit in the Stages, revealing potential sources of error in data recording or sampling within power meters.

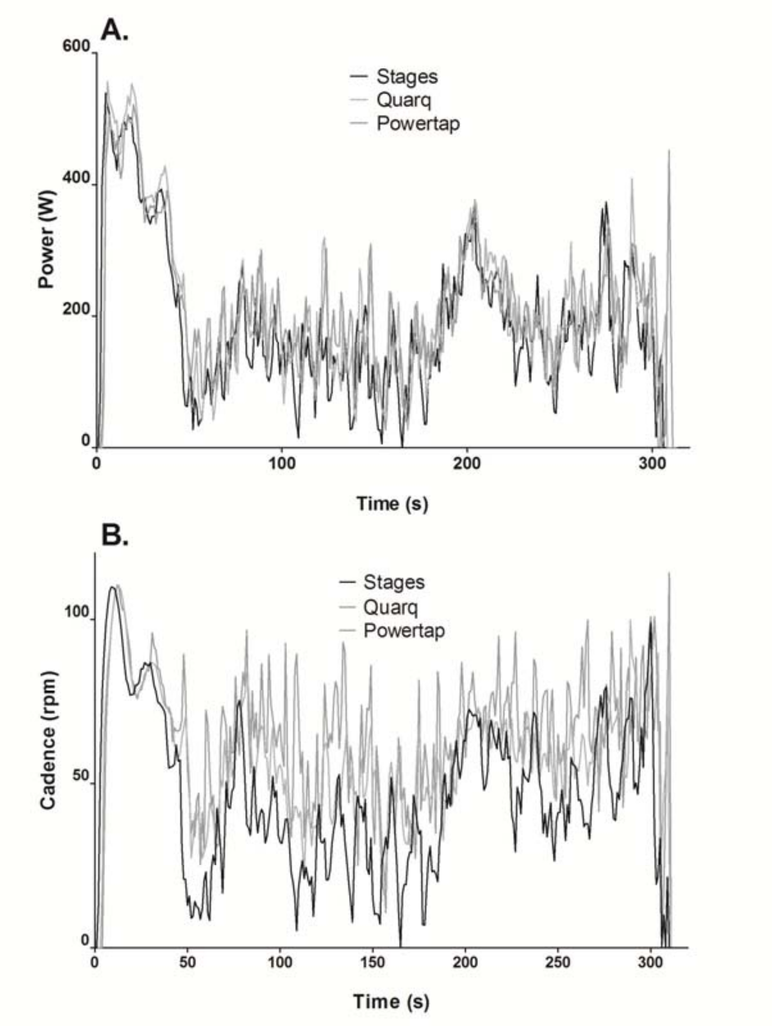

Figure 4. A. Power (W) and B. cadence (rpm) graphs for XCO-MTB lap with all power meters.

Discussion

The primary aim of this study was to assess variability between power meters used in XCO-MTB. The main findings of this study are that: a) power recordings during smooth, steady riding are not significantly different regardless of power meter used, and are robust regardless of cadence; b) mean power is not significantly different between the Quarq and Powertap overall, but both are significantly different than Stages during a varied terrain off-road lap; c) recordings reflecting the duration of coasting are significantly longer in the Stages power meter compared with the Quarq and Powertap.

The results of this study clearly indicate some variance between different makes of power meters rather than indicating which shows a more accurate reading, as the determination of the most accurate power meter requires a CALRIG as used previously (Gardner et al., 2004). Even the SRM power meter, often used to compare other power meters against (Bertucci et al., 2005; Gardner et al., 2004; Hurst et al., 2015; Millet et al., 2003; Sparks et al., 2015) has a manufacturer stated error of over ±2% for the ‘Professional’ model, therefore, the SRM was not used to compare power meters against in this study. Further, a comparison of the Powertap and SRM power meters has revealed large variation in accuracy across individual power meters even within the same make (Gardner et al., 2004). For these reasons, in the current study it was decided that each power meter should be assumed as accurate as the other according to manufacturer’s claims, but that recordings should be compared to indicate any potential difference and reasons for these.

All power meters were able to reflect average power not significantly different from the others as well as similar average cadence during smooth riding at a fixed speed, regardless of whether the trial was high or low cadence. This indicates that measuring power via these three power meters should not produce significantly different results during steady riding and suggests that any major differences would come about during intermittent cycling. As such, it does not appear that the Stages grossly over- or under-estimates power when power is measured at only the left leg and assumed proportional to that of the right, nor does it suggest that either of the three power meters are less or more acceptable for steady riding. Given previous research on the Powertap (Bertucci et al., 2005; Gardner et al., 2004), this would tend to suggest that both the Stages and Quarq are useful and acceptable for steady cycling. The Powertap power meter had two instances of two seconds each which reflected zero power and cadence readings during the high cadence trail for two participants, however this was not ignored for analysis as this has been observed previously (Gardner et al., 2004).

Power and cadence graphs (Figure 4) indicate differences in measurements, but do not indicate a phase delay in the Powertap as seen previously (Gardner et al., 2004). Despite being synchronised properly, recordings in the Stages do seem to precede those of the Quarq and Powertap. The Quarq and Powertap did not produce power recordings different from each other in any section of the XCO-MTB lap (Figure 2), but both were different from the Stages in all sections off-road. However similar power recordings were between the Quarq and Powertap, the results show significant differences in cadence between all power meters in the DH and FLAT, which may be exacerbated by a higher frequency of coasting as seen in the frequency distribution (Figure 3). Conversely, greater agreement in power and cadence in the UP section, illustrated by the least significant observed differences between the Stages and both Quarq and Powertap, could be due in part to this section having the lowest frequency of coasting. Suggestively, it does appear that a higher frequency of coasting tends to complicate the comparison of measurements between power meters.

Further analysis indicates that the Stages produced more zero (0) values for power and cadence during all sections of the XCO-MTB track, reflected by lower overall mean power and cadence off-road. Following analysis of coasting, a longer duration was found in the Stages than the other power meters. Interestingly, the Stages was the only power meter to have a correlation coefficient of 1.0 between cadence and power coasting duration, indicating robustness in recorded values, while both the Powertap and Quarq had periods of time with 0 W corresponding with > 0 rpm or 0 rpm corresponding with > 0 W. Collectively, it is surmised that a large part of the variation in the readings produced by these power meters is based on the ability to instantaneously sense rotation of the cranks or estimate the rotation of the cranks at the rear wheel.

Potential differences in ability to reflect actual cadence -and thus power- could be due to the different methods utilized to measure cadence in the three power meters used in this study. Indeed the methods of a magnet fixed on the bicycle frame (e.g. Quarq) and an indirect measurement within the hub (e.g. Powertap) may be viewed as less technologically advanced than an accelerometer built into the crank (e.g. Stages), however, it is not known how this accelerometer is affected by high frequency vibrations seen in XCO-MTB, as similar devices have been used to quantify vibrations in cycling (P. W. Macdermid et al., 2014). It is important to point out that when riding off-road, riders are often changing pedal position to avoid hitting obstacles or shift weight about the bicycle to maintain traction. As these can be quick movements, it is possible that a quick forward-backward-forward movement of the cranks could produce an artificially over-estimated cadence reading in some or all of these devices. This warrants further research, but does indicate that manufacturers must provide products that are accurately able to reflect cadence.

Conclusion

Results of this study suggest that despite strong agreement during steady cycling, differences in power readings between power meters may lie in ability to measuring cadence, especially with respect to reducing to or surpassing zero during highly intermittent XCO-MTB. Overall there is no reason to suggest that the Stages, Quarq, or Powertap are better than the each other; as such, consumers should choose the device that is most practical with low overall weight and cost. Manufacturers must focus on providing products that are accurately able to measure cadence when used to determine power.

Disclosure Statement

The authors maintain there is no conflict of interest in this study.

MASSEY UNIVERSITY
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STATEMENT OF CONTRIBUTION TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Matthew C Miller

Name/Title of Principal Supervisor: Prof Stephen R Stannard

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In which Chapter is the Published Work: Appendix I

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate: 90%

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Data collection and analysis; manuscript drafting; manuscript submission

Matthew C Miller Digitally signed by Matthew C Miller Date: 2017.08.21 13:38:58 +12'00'
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