Using field based power meter data to model track cycling performance

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Abstract

Track cycling events, both sprint and endurance, are primarily focused on performance of high and medium power durations, and it is suggested, measures of peak power govern performance in the sprint and pursuit cycling events. Various tests and metrics in the laboratory have been used to try and model track cycling. With the advent of power meters cyclists have been able to record power output in the field and several basic tests have evolved to use as a means to get started with training and racing with power.

This thesis proposes a linear model based on total least squares regression, to evaluate these models and provide an option for coaches to see what durations are key for performance, and for sprint cyclists what types of training should be performed at a given part of a training build up. This analysis is applied to sprint cycling, male and female sprint cyclists, and pursuit cyclists to evaluate field-based data compared to lab and model derived metrics.

The key conclusions from this thesis are:

1. For each specific power duration along the hyperbolic power-duration curve shows field-based data offers a better model for both sprint and pursuit durations. The linear model has a parabolic relationship the closer the inputs get to the specific duration assessed.

2. This disproves the contention of a linear process governed by peak power being the key metric of sprint cycling. The data in this thesis shows not only is this relationship incorrect, but strong relationships with sprint cycling durations hold for durations as long as 20-min.

3. This thesis finds there are sex differences for the model showing women have a higher variation of sprint power than men.

4. The linear model is applied to track endurance cycling to show, again, how a peak power (or maximal sprinting power or $\dot{V}O2_{max}$) does not govern performance, more a broad base of capacity reflected by a high lactate threshold, ventilatory threshold, critical power or other estimates of the maximal metabolic steady state.

5. Based on an understanding of the importance of capacity as well as peak power Chapter 6 shows this information can successfully be applied to the performance of sprint cyclists training towards peak performance.

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List of Abbreviations

ANOVA	Analysis of Variance
APR	Anaerobic Power Reserve
ASR	Anaerobic Speed Reserve
ATP	Adenosine Triphosphate
BAL	High Intensity Energy Balance
BMX	Bicycle Moto Cross
CFD	Computational Fluid Dynamics
CP	Critical Power
END	Endurance Athletes
FTP	Functional Threshold Power
GPS	Global Positioning Satellite
HIIT	High Intensity Interval Training
IQR	Inter Quartile Range
LT1	First Lactate Threshold
LT2	Second Lactate Threshold
MAP	Maximal Aerobic Power
MMSS	Maximum Metabolic Steady State
MFT	Muscle Fiber Typology
NIRS	Near-infrared Spectroscopy
PAP	Post Activation Potentiation
PC	Phosphocreatine
PDA	Personal Digital Assistant
PO	Power Output in Watts
PPO	Peak Power Output in Watts
R^2	Coefficient of Determination
RSA	Repeated Sprint Ability
SIT	Sprint Interval Training
SRM	Schoberer Rad Meßtechnik brand Power Meter

TLS	Total Least Squares Regression Model
TT	Time Trial
U17	Cycling NZ Under 17 years of age grade
U19	UCI Under 19 years of age grade
UCI	Union Cycliste Internationale
VT1	First Ventilatory Threshold
VT2	Second Ventilatory Threshold
$\dot{V}02_{max}$	Maximum Oxygen Uptake
$\dot{V}0_{2peak}$	Peak Oxygen Uptake
W’	High intensity energy, measured in kJ
W’bal	High intensity energy balance
WADA	World Anti-Doping Agency
WKO5	Brand of Sporting Power Meter Analysis Software

Publications

This thesis is based on 5 publications where Hamish Ferguson was the lead author and contributed to over 94% of work in each publication.

H. A. Ferguson, C. Harnish and J. G. Chase, **Using Field Based Data to Model Sprint Track Cycling Performance**. Sports Medicine - Open 2021 Vol. 7 Issue 1 Pages 20

H. A. Ferguson, C. Harnish and J. G. Chase, **Reply to: Comment on: “Using Field Based Data to Model Sprint Track Cycling Performance”**. Sports Medicine - Open 2021 Vol. 7 Issue 1 Pages 61

H. A. Ferguson, T. Zhou, C. Harnish and J. G. Chase, **Model of 30-s sprint cycling performance: Don’t forget the aerobic contribution!** IFAC-PapersOnLine 2021 Vol. 54 Issue 15 Pages 316-321

H. A. Ferguson, C. Harnish, S. Klich, K. Michalik, A. K. Dunst, T. Zhou, and J.G. Chase, **Power-duration relationship comparison in competition sprint cyclists from 1-s to 20-min. Sprint performance is more than just peak power.** PLOS ONE 2023 Vol. 18 Issue 5 Pages e0280658

H. A. Ferguson, C. Harnish, S. Klich, K. Michalik, A. K. Dunst, T. Zhou, and J.G. Chase, **Track cycling sprint sex differences using power data**. PeerJ 2023 Vol. 11 Pages e15671

Preprints

Ferguson, H.; Harnish, C.; Chase, J.G. **Performance Progression over a Three Months of Periodized Training for Track Cycling Sprinters.** *Preprints* 2023, 2023071992.

Other publications within the study period…

C. R. Harnish, H. A. Ferguson and G. P. Swinand. **Racing Demands of Off-Road Triathlon: A Case Study of a National Champion Masters Triathlete.** Sports 2021 Vol. 9 Issue 10.

Presentations

Ferguson, H. **Model of 30-s sprint cycling performance: Don't forget the aerobic contribution!** IFAC Conference, 21 September 2021, Ghent, Belgium (online).

Chapter 1: Introduction

This thesis explores the sport of track sprint and track endurance cycling. It begins by talking about the advantages of riding, track cycling, and sprint cycling competitions in velodromes in terms of the data available to both riders and coaches. This initial discourse provides a foundation for demonstrating the need for scholarly investigation to optimize rider training and performance.

1.1 Sport

Sport, which includes a wide variety of physical activities and competitions, has been a fundamental aspect of human society for ages. Sport has evolved and transcended geographic boundaries, social systems, and cultural distinctions from ancient civilizations to the present. A complex interaction of physiological, psychological, and socio-cultural elements is required to perform at one's best in sports. To outperform their rivals, athletes work to maximize their physical prowess, mental concentration, and strategic thinking. It is essential for coaches, sports scientists, and athletes to comprehend these elements.

Physiological characteristics, such as cardiovascular health, strength, speed, agility, and endurance, have an impact on physical performance. These physical qualities can be improved using training techniques including periodization and targeted conditioning regimens. Altitude training, biomechanical analysis, and nutritional strategies are a few examples of advances resulting from developments in sports science which have enhanced human performance [1, 2].

The performance of an athlete is influenced by psychological aspects. The fundamental psychological traits of mental toughness, focus, motivation, and confidence can make a substantial difference in competitive situations. Sports psychology has become a unique science, offering methods like goal setting, visualization, and mindfulness to improve mental fortitude and improve performance results [3-5]. An athlete's experience and performance are shaped by social support, cultural expectations, and society conventions [6]. Performance levels between people and nations can vary depending on specific aspects, such as access to resources, infrastructure, and training facilities, as well as cultural factors and beliefs.

Sports performance analysis has been transformed by the development of technology [7, 8]. Athletes and coaches can gather information, pinpoint areas for growth, and make decisions using tools like wearable technology, video analysis software, and data-driven performance measurements [9, 10]. Additionally, improvements in sports medicine and methods for preventing injuries have improved overall performance outcomes by lengthening athletic careers [11-19].

1.2 Cycling

The earliest known bicycle, the "dandy horse," originally debuted in the early 19th century, which is when cycling first became popular. The pedal-driven bicycle, created in the 1860s, served as the inspiration for the modern bicycle. It was not long before competition emerged, and organized bicycle races first appeared in the late 19th century, leading later to the establishment of national and international cycling federations. The first Tour de France, held in 1903, was a turning point for the sport, establishing the foundation for modern-day professional road cycling.

Technology of all types has enhanced cycling and improved performance independent of the athlete. By enhancing durability, lowering weight, and increasing stiffness, bicycle frames have evolved from heavy steel to lightweight materials like aluminum and carbon fiber, improving performance [20-22]. With the advent of derailleurs and multi-speed gear systems, cycling underwent a revolution, enabling riders to adjust to diverse terrains and ride at various cadences for less overall effort, again improving performance. Efficiency and precision were increased even further with the development of electronic shifting systems, and the ever-increasing number of gears which can be installed on a bicycle. Further, developments in aerodynamic design, including the use of computational fluid dynamics (CFD) and wind tunnel testing, has led to streamlined helmets, wheels, and frames, all of which have greatly decreased air resistance and increased overall speed [23-26].

Cycling training methodologies have developed over time, combining both scientific concepts and empirical evidence [1, 2, 27-33]. Power meters and heart rate monitors have made it possible to precisely measure and analyze training loads, improving performance, and reducing overtraining. Thus, both empirical and technology-based training methods have emerged and joined forces in more recent years to enhance performance [34].

Sports science and nutrition have also advanced due to the application of sports science to cycling. In particular, the fields of biomechanics, physiology, and nutrition, have all led to improved athlete and cyclist performance [1, 2, 35]. Cycling enthusiasts have, in turn, refined their training plans, non-cycling training, and diets to maximize performance and recovery by understanding the demands of the sport [1, 2, 36].

Performance-enhancing drugs have been used by athletes in the cycling sport, which has had its share of doping scandals [12, 37-44]. To promote fair competition and safeguard the sport's integrity, strict anti-doping procedures have been put in place, such as the creation of the World Anti-Doping Agency (WADA) and biological passport systems. While these do not enhance performance, they try to ensure integrity in the competition.

Over the years, cycling has seen major changes, with scientific discoveries and technological developments being crucial to improving performance. Cycling's development from a simple mode of transportation to a fiercely competitive sport has created a rich history. This chapter offers a thorough account of cycling's progress by analyzing the historical context, technological developments, and performance improvements. The goal is to highlight cycling's multifaceted nature as a sport, integrating history, technology, and human achievement. The subsequent sections discuss the overall history of track cycling on a velodrome, and its sub-specialties in track sprinting and endurance events.

1.3 Track cycling

Cycling on the track is an intriguing sport mixing endurance, strategy, and power / speed. This section offers a thorough examination of track cycling covering the sport's historical history and examining the elements arising from this history which influence elite performance and coaching today. A thorough discussion of performance variables, such as training techniques, equipment optimization, and physiological demands is a necessary precursor to the research presented in this thesis.

Track cycling dates to the early 19th century, at the same time as the bicycle was invented. The first known cycling competition was held in 1868 at Paris' Parc de Saint-Cloud, which helped to establish the sport's later popularity. Velodromes, or specialized tracks, were eventually constructed to meet the needs of track cycling.

The creation of the International Cycling Association (ICA) in 1892, which sought to coordinate and control cycling competitions globally, boosted the growth of track cycling a boost. This development of cycling in general, opened the door for track cycling to be a part of important international events like the Olympic Games and World Championships.

The development of track cycling has also been influenced by technological improvements. Speed and effectiveness increased with development of aerodynamic helmets, lightweight frames, and high-performance materials. The use of indoor velodromes with controlled conditions lessened the impact of outside influences on performance, raising the level of competition in the sport. All these changes have distilled track cycling performance to a truer comparison of human performance between riders by reducing the influence of external forces and conditions.

Track cycling performance improvement necessitates a comprehensive strategy accounting for all the variables affecting success. These elements can be broadly divided into three categories: training strategies; equipment optimization; and physiological requirements [45-47]. Each category seeks to optimize a different rider element to maximize their racing outcomes.

Track cycling training regimens have changed significantly over time. A crucial component of track cyclists' training is high-intensity interval training (HIIT), which involves short bursts of maximum effort alternating with recovery periods [48-53]. Building aerobic and muscular endurance also requires endurance training, which includes tempo and long-distance rides, all of which may contribute to both endurance capacity, as well as peak power [54-57].

Track cycling has made equipment optimization crucial, because even the tiniest changes can have a big impact on results. To improve aerodynamic efficiency, bicycles are painstakingly built and engineered with components like streamlined frames, deep-section carbon wheels, and optimum gear ratios [58-61]. Additionally, improvements in bike fitting methods, motion capture analysis, and wind tunnel testing assist athletes in finding the best riding positions to reduce drag [62, 63].

Sprint competitions call for anaerobic endurance and explosive power, with a focus on fast-twitch muscle fibers [34]. In contrast, endurance events call for sustained effort over longer distances and effective oxygen usage [64, 65]. Track cyclists engage in specialized strength and conditioning programs designed to improve the necessary physiological characteristics to meet these demands [66-70].

The optimization of track cycling performance requires careful consideration of diet and recovery methods [71-73]. Timing of nutrients, adequate hydration, and fueling help sustain energy levels and support muscle regeneration [74]. To avoid overtraining and lower the risk of injuries, sufficient rest and recuperation times are also necessary [75-77].

1.4 Track Sprinting

Sprinting on the track combines power, speed, and strategy to succeed on the velodrome. Sprint cycling on velodrome tracks was developed from early bicycle racing in the late 19th century.

Cycling competitions could be held in a regulated setting thanks to the advent of indoor velodromes, which led to the emergence of sprint-focused competitions. An important turning point in the history of track cycling sprinting occurred in 1893, the year of the first officially acknowledged world championship.

Equipment and technique underwent significant changes because of advances in technology and the understanding of aerodynamics over time. Performance was improved through advancements in frame design, gearing, and tire materials from the earliest high-wheeler bicycles to the introduction of the safety bicycle. Track cycling sprinting was further transformed with the development of clipless pedals, aero handlebars, and lightweight materials, allowing riders to sprint more effectively and efficiently [64, 78-81].

Sprinting on a track requires great speed and powerful acceleration. Through a combination of physical strength, anaerobic capability, and efficient pedaling technique, riders produce very high power [34]. For the duration of the race, maintaining peak speed while accelerating requires the ability to output high power in brief bursts [82-87]. Minimizing air resistance by reducing drag using minimal air resistance components and optimizing rider position is thus also crucial.

Sprinting on the track requires tactical skill, as well. A typical tactic is to draft, which involves positioning oneself behind an opponent to lessen wind resistance [24, 88-90]. Timing and placement are essential because sprinters frequently use psychological strategies to outdo their competitors [91]. The key to winning is having the ability to read the race, foresee opponents' moves, and execute well-timed strikes.

While the focus of sprinting on the track is mostly on explosive power, some degree of endurance is also required [92-94]. In races like the keirin or team sprint, riders must have the strength and endurance to maintain high speeds across several laps. A sprinter's physical endurance is built by a combination of rigorous cycling training, including intervals and resistance training.

Sprinters use a variety of methods, tools, and approaches, which have been formed by the historical history of the discipline, as well as numerous performance criteria. Track cycling sprinting success requires the fusion of power, speed, aerodynamics, tactical awareness, strength, endurance, and psychological fortitude. The planning of preparation for sprinters draws on a wide range of training methods and planning approaches [34].

1.5 Track cycling endurance competition

Track endurance cycling poses a distinct set of difficulties. The velodrome's banking curves, which can place great stresses on the body, require riders to maintain a high degree of speed and power [95]. High-speed maneuvers and frequent acceleration and deceleration make perfect bike handling abilities necessary in addition to physical strength.

Endurance requires the consistent delivery of power output over lengthy periods of time. This feature of the sport is best illustrated by the individual pursuit, a timed competition in which cyclists compete against the clock alone [64]. To perform at their best, riders must strike a careful balance between pacing and exerting their greatest effort.

1.6 Modelling Track Cycling

To perform at their best, athletes and coaches are always looking for ways to increase their speed, power output, and general effectiveness. Performance models have become essential resources in the world of track cycling sprinting for meeting performance targets [27, 96]. These models offer important insights, support training optimization, and aid in the creation of new methods and strategies by fusing science and data analysis. In this thesis, the use of performance models to sprinting in track cycling and their effects on athlete performance is the primary focus.

Performance models are frameworks to analyze and forecast many facets of an athlete's performance [27, 64, 97, 98]. These models simulate and analyze the variables influencing sprint performance using equations, physics, and substantial amounts of data. They provide a thorough analysis of athletic performance potential by accounting for elements including power output, aerodynamics, gear selection, pacing techniques, and physiological parameters [34]. Performance models can assist trainers and coaches in customizing training programs for each athlete by analyzing their physiological capabilities. By simulating different training settings, these models can pinpoint the best practices for enhancing power output, speed, and endurance.

Coaches can assess the effects of various training interventions and decide on their training program with the use of performance models. For instance, the coach can assess how changing training volume, intensity, or recuperation times will affect their athlete's performance. This data-driven methodology helps reduce the chance of overtraining and maximizes the effectiveness of workouts, which results in improved performance gains. Thus, models benefit both athletes and coaches to optimize performance.

As new data and technology become available, performance models are changing and adapting [98-101]. They function as a proving ground for novel concepts and methods, enabling the investigation of novel tactics which can improve performance. Athletes and coaches can evaluate the viability and impact of these unique ideas by simulating the possible results before putting them into practice during actual competition. With this knowledge of cycling performance, athletes can make data-driven choices which will offer them an advantage in competition [27, 97].

Finally, modelling track cycling endurance competitions is an intriguing nexus of sports science, mathematics, and technology. These models enable athletes and coaches to choose the best training, pace, and equipment by revealing the complex interplay of factors affecting performance. The combination of data-driven insights and human agility promises to push the limits of track cycling to new heights as technology advances [102-106].

1.7 Problem Statement

Current models of track sprint and track endurance are based on general models, which are currently insufficient to describe actual competition performance. This thesis hypothesizes:

1. There is a parabolic relationship to event specific power in comparison to general power, disproving the notion of a linear relationship where a peak power acts as a governor to performance, and thus its primary determinant.
2. The linear model applies to sprint cycling, disproving the notion of peak 1-s power being the primary driver of sprint cycling performance.
3. There are sex differences in performance between male and female sprint cyclists.
4. The linear model applies to track endurance cycling, disproving the notion of either

peak power or power at the $\dot{V}O2_{max}$ driving performance.

5. The linear model provides valuable information to assist a coach in prescribing exercise towards peaking for a key sprint cycling event.

1.8 Preface

This thesis is comprised of several original studies in main body chapters, outlining the sports science studies and analyses undertaken. They seek to address each of the main questions outlined in a structured format. In particular:

Chapter 2: Surveys the current models of sprint and endurance cycling performance, and the physiology underpinning. Key models/tests of track cycling performance include:

1. The Wingate test measuring the all-out capacity of the cyclist.
2. Anaerobic Power Reserve is based on the running version, anaerobic speed reserve, which uses maximum sprinting speed, and maximal aerobic speed and a coefficient to estimate speed, or in cycling, power, to estimate performance over 1-s to 300-s.
3. Critical power is primarily used to predict power in the severe exercise domain, effectively between the lactate threshold and the $\dot{V}O2_{max}$, However the model does allow the prediction of finite high intensity energy above the critical power, which applies to the high intensity nature of track cycling.

Chapter 2 shows how none of these models perfectly, or even necessarily adequately, predict performance, and none make any readily usable physiological measures useful to coaches. They do allow measurement of performance in the field and do not require invasive methods. Based on the gaps in performance modelling and outcomes in the field, current models of track cycling performance were evaluated alongside the linear model.

Chapter 3: Investigates the relationships between 15 and 30 second power and longer durations, up to 20-min using 4 different models: exponential, linear, parabolic and a power equation, finding a linear model showed the relationships track cycling durations, and durations more commonly associated with endurance performance stayed high, suggesting a synergy between sprint and endurance performance. From the linear model, the line of best fit was used to describe riders who were above the line who were strong in peak power, and riders below the line, who were strong in capacity.

Chapter 4: Compares measures of peak power and endurance performance with 15-30 second power and showed a parabolic relationship between both peak power and longer duration sprint durations, and again, as in study one, the relationships between endurance performance and sprint cycling stayed high. In terms of training priorities this data suggested efforts of 15-30 seconds were the primary focus of improving performance and showed efforts of 45-60 seconds were as equally as related to specific durations of track cycling sprint performance as measures of peak power. As in study one the relationship between measures of track cycling sprint power and endurance power (up to 20-min) stayed strong, $R^2 > 0.82$ and positive suggesting endurance riding would benefit sprint cycling performance.

Chapter 5: Investigates sex differences in track cycling sprint cyclists and found there were no differences in the relationships between different durations associated with track cycling performance, however there was greater variability in the female group suggesting the importance of using the line of best fit model to focus training to each athlete's needs.

Chapter 6: Applies the model to a group of track sprint cyclists over three x four week training blocks progressing towards a key track cycling sprint event and showed those athletes who started below the line (strong capacity in relation to the line of best fit) and progressed towards a balance of peak power and capacity in the 2nd block and in the final block pursued peak power and capacity maintenance made the highest gains, while the athletes who were strong in peak power, and kept focused on peak power made the smallest gains.

Chapter 7: Compares field-based data with the total least squares model based around track sprint durations (15 – 30 seconds), anaerobic power reserve, critical power: asymptote and *W'*, over several durations. Strong correlations were seen, with the strongest coming from the field-based data, thus showing no major advantage from specific testing procedures.

Chapter 8: Investigates the model for durations around the track endurance events (1-min, 2-min, and 3-min), anaerobic power reserve, critical power (asymptote and *W'*). Again, strong correlations were found for all the models and the models derived from field measures were just as effective as complicated tests of track cycling endurance performance.

Chapter 9: Applies the model to the bunch races where a rider needs a mix of attributes from race winning speed, ability to pursuit away near the finish, or the ability to try and lap the field on the bunch. Hence, the linear model for 30-s, 3-min and 8-min is compared to the critical power model (CP) and the *W'* component of CP. The linear model is evaluated against the 20-min x 0.95 estimate of the functional threshold power, a simple one-off test.

Chapters 10 and **11:** Present the overall thesis conclusions and future work.

Chapter 2: Using field-based data to model track cycling performance

Content presented within this chapter has been published as:

H. A. Ferguson, C. Harnish and J. G. Chase, **Using Field Based Data to Model Sprint Track Cycling Performance**. Sports Medicine - Open 2021 Vol. 7 Issue 1 Pages 20

2.1 Introduction

Originating in the 1870's, track-cycling flourished due to the confined *velodrome* environment, which allowed for charging admission, betting, carnivals, and partnerships with other sporting and entertainment events. So popular was the sport, it was included in the inaugural 1896 Olympics [107]. While velodromes can vary widely in construction and location, track cycling at elite world level events takes place only on indoor velodromes.

Sprint-cycling takes place over short distances, involving team, individual, and bunch races with groups from two to seven competing. Table 2.1 describes the four sprint cycling events raced at World Championship level, where the time trial event is no longer part of the Olympic program. Like road cycling, performance is influenced by environmental demands, rider related factors, and mechanical inputs [108], however, the controlled environment provides an analytical advantage, where reproducible measures of cycling performance may be obtained. Track sprinting can be assessed quantitatively by the results attained, times performed, bicycle and wearable sensors, and more recently, direct power output measurement. To fully elucidate performance, and thus adequately model performance, direct measurement of both mechanical and physiological variables are needed.

Table 2.1: World Championship Sprint Cycling Events

Event	Description	Race Format
Team Sprint*	Teams of 3 riders complete over 3 laps where position 1 leads for first lap and pulls aside to allow position 2 to take the lead for a lap and the third rider completes the final lap.	N = 3 rides in 1 session (1/2 day) • Qualifying round • Round 1 • Final: Gold and Bronze Medals
Match Sprint*	After a seeding, round riders are matched, top seed vs. lowest seed through rounds in knockout rides. Each ride is over 3 laps where the riders jockey for position before racing to the line. From the quarter finals the knockout is from best of three rides.	N = min 9 ride, max 12 • Seeding Round • 1st round • 2nd Round • Quarter Final (best of 3 rides) • Semi Final (best of 3) • Final (best of 3)
Keirin*	Raced over 6 laps the first three are paced up to speed by a motorized cycle which pulls off the track with 3 laps to go and the rider race for placings.	N = min of 4, max 5 • 1st round • Repechage • 2nd round • Semi Final • Final and Minor Final
500-m (Women) /1000-m (Men) Time Trial	Rider's race against the clock for the distance. They start from a gate connected to the timing system. From 2025 Women will compete over 1000-m.	N = 2 • Qualifying • Final

* = Olympic Events

The advent of the power meter, allows rider, coach, and sport scientist to assess performance in the field with physiological responses, as well as in exercise in the laboratory [109-112]. High quality power meters have been validated against a calibrated ergometer, and against other brands of power meter [111, 113-118], and allow the user to calibrate the meter, ensuring valid and reliable data [113, 119-121]. Riders, coaches, and sport-scientists use this data to improve decision-making around the preparation of riders for future events.

Power meters provide direct measures of power supply / demand while riding, to create data-led models of performance [98, 108-110, 112]. The ability to measure power, heart rate, GPS data, and more, has given rise to numerous online, and stand-alone platforms displaying rides, tables summarizing data, and large numbers of derived metrics, which all attempt to model acute and chronic performance. However, these models only estimate supply and demand for a given moment, neglecting the huge amount of variation as a function of different velodromes, competitions, events, racing environments, and critically, individual physiology models [97, 122-124].

Fig. 2.1 outlines the basic supply and demand variables of sprint-cycling performance. In doing so, the goal is to determine the optimal components of sprint performance, and importantly, those which might be missing. This review chapter focuses heavily on the physical data obtained from a cycling power meter. However, a comprehensive model of cycling also involves the technical, tactical and psychological event demands, as well as rider physiological characteristics [125]. The outcome should enhance the ability to use power meter data and physiological measures to model sprint-cycling, to guide coaching and optimise performance.

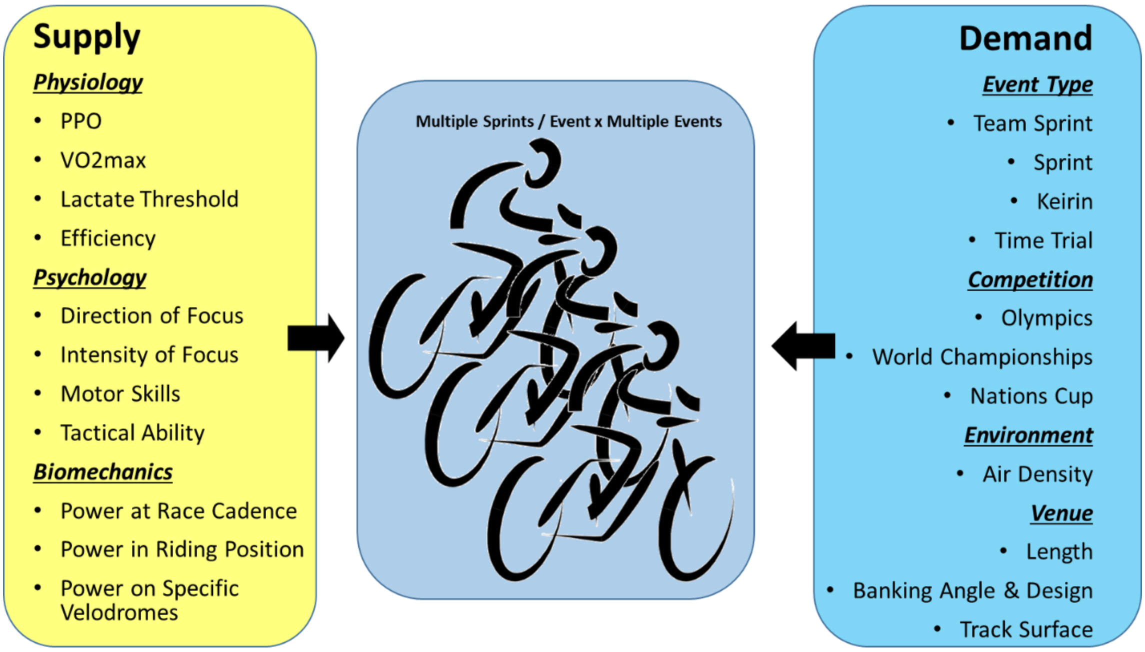

Fig. 2.1: The supply and demand characteristics of track cycling in a multiple sprint and potentially multiple event competition.

2.2. External demands of sprinting

Variables riders encounter include venue characteristics, atmospheric conditions, rider trajectory, aerodynamic drag of the bicycle and rider, mass and inertia, mechanical efficiency, rolling resistance, and properties of tires [98]. Demand is estimated by measuring the power required to compete at a given level. Optimization is achieved when the power required to overcome event and location specific demands is reduced for the given level. Appreciation of these demands, between differing track shapes, track surfaces, conditions, and competitive scenarios are an important part of understanding the power required to compete in each event and location, and thus directly impact the training required to prepare for those demands.

2.2.1 Venue Characteristics (Velodromes)

Across the spectrum of venues, velodrome characteristics can vary widely. At Elite World Championships and Olympic Games, however, velodrome surfaces are typically constructed of wood, and lap distance is standardized to 250-m. At Junior World Championship level, velodrome size may also include tracks of 200, 285, and 333.33 metre distance. The length of straights and bends, steepness of the banking and straights, and transitions in and out of the bends, can vary [98]. Riding on the banking, and transition from bends to straights, play a role in physical, tactical, and technical performance, meaning average power may not accurately estimate competition demands [126].

2.2.2 Air Resistance

Aerodynamics play a major role in determining velocity at a given power-output [79]. The coefficient of drag multiplied by frontal surface area (C_dA), can be measured using a wind tunnel, and also estimated using virtual elevation (VE) from power meter data [127-131], and comparisons between wind tunnel and models based on velodrome data are favorable [128, 132, 133]. Frontal area of the bicycle and rider at 40-kph comprise ~75% of resistance, rising to ~95% at 60-kph [134, 135]. While there is benefit from riding in an aerodynamic position, there can be a trade-off with power output, with the final balance determining speed [25, 108, 136-138]. Air resistance is reduced in mass-start and team sprint events, as riders draft behind other riders, saving as much as 30% of the energy required to race at the front of a group [24, 88, 89, 139-141].

2.2.3 Rolling Resistance and Riding Surface

Rolling resistance, determined by velodrome riding surface, tire construction, inner tube composition and tire pressure has a measurable effect on performance [98, 142-144]. On an indoor velodrome with steeply banked ends, slip variables and friction of the riding surface impact riding through banked ends, transitions into and from bends, and steer angles. These factors all influence power requirements and performance [98]. Power meter measurement can be used to estimate the effects of different tire pressures on rolling resistance [129].

2.2.4 Summary

The primary takeaway points from this section related to power requirements in sprint cycling include:

- The external demands of track sprinting can vary between velodromes but will be consistent for all riders and measurable with a power meter in controlled conditions.
- These external demands can be directly related to the peak and endurance power required to compete for a given event and provide a minimum consistent requirement for an event.
- Aerodynamics and positioning are the external power demands most likely to impact performance, as well as the most likely to be coached, given the similarity in other factors across all racers.

2.3 Peak Power Output

Once the demands of sprint track cycling are understood it is important to assess the rider to determine which areas of racing and training they should devote their energy towards. Considering the short durations of sprint events, strength, power and a strong anaerobic capacity are key attributes.

2.3.1 Application of PPO to Sprint Cycling

Peak-power output (PPO) is the maximal power generated by the athlete and is measured in watts. From a power meter PPO is derived by multiplying average effective pedal force by the cumulative pedal frequency and the length of the crank (torque * cadence * crank length) [113, 145, 146]. Linear estimates of power are measured from accelerometers, cables attached to an athlete or weights bar, and force plates [147, 148]. PPO is considered the key metric in sprint cycling and based on the anatomy and physiology of athletes. Thus, various models have been developed to understand and estimate the effects of PPO variables [128, 149, 150]. However, to date, none of these models are used to model actual sprint competition.

The challenges of measuring PPO are differences between power in the saddle and power out of the saddle, type of start performed, and the position of the rider on the track. Measures of power-delivery while seated, were lower than out of the saddle, owing to differences in cadence [151]. Additionally a 4-s test found a higher PPO than the Wingate Test [152], and a comparison of short starts in BMX, with similar PPO to track sprinting, showed the standing jump test, bicycle start down a ramp, and flat start PPO was: 1935±519W, 1817±383W, 1662±365W respectively [153]. Maximal power has been predicted by pedal rate, muscle size, fiber composition and fatigue [154], but not for the slope of the start, which could be relevant as sprints can often begin using the slope of the velodrome bankings.

2.3.2 Anatomy and Physiology of PPO

The underlying anatomy and physiology of sprinters can be measured, to guide event selection, training and event strategy [155-158]. Traditionally, muscle biopsies have been used to measure the anatomical and biological differences between athletes [159]. More recently, magnetic resonance imaging [156, 160] and ultrasound [161-164], have offered easier less invasive measurement options.

Differences in muscle thickness are observed between sprint and endurance cyclists [163]. In a study of cyclists' quadriceps and hamstrings, muscle volume and pennation angle were related to peak-power, but not fascicle length [156]. Ankle-extensor force had very little influence on PPO (r=-0.03), while hip-extensor (r=0.56) and knee-flexor (r=0.53) force were moderate predictors' in contrast knee extensor force (r=0.71) and isometric cycling specific torque of the knee extensors (r=0.87) were more strongly associated to PPO [165]. Peak-power was predicted by quadriceps and gastrocnemii cross section area, whereas fascicle length of the vastus lateralis predicted both peak power and time to peak-power [164]. In review, while anatomical structure can explain differences in PPO between sprinter and endurance cyclists, evidence is lacking on whether PPO differentiates sprint race performance.

2.3.3 Summary

The primary takeaway points from this section include:

- Peak power is easily measured in the laboratory and in the field using a power meter.
- PPO and other similar peak power training metrics may not be an optimal training goal or representation of sprint cycling performance given the repeated efforts required in sprint cycling competition.

2.4. 15-60s Sprint Performance

While PPO is the measured used to assess sprint cycling performance in current coaching, Table 1 clearly illustrates sprint-cycling competition ranges from 15-60-s, is not adequately modelled by PPO. Additionally, it must also be noted all events require repeated efforts with short recovery times. Thus, there is an increased oxidative component to sprint competition. This section reviews the energy systems involved in sprints of 15-60 seconds duration.

2.4.1 Energy pathways for sprint cycling

The shortest events and sub-components of track-sprint cycling are the flying 200-m used to seed the sprint event, where timed duration is around 9-11 seconds. However, actual duration from the jump off the banking to finish line is ~18-20 seconds [166], and position one of the team sprint races for 16-22 seconds. Typically, events are raced over 20-35 seconds depending on race type and individual race tactics. Moreover, position three of the team sprint and the Keirin often raced over 30-50 seconds. Hence, this section explains the implications of maximal efforts over these durations and differentiate them from measures of peak power.

The Wingate test is the most used measure of a single sprint-cycling [167, 168]. The test is commonly performed over 30-s, but may range from 4-60-s. From the Wingate test: PPO, time to PPO, average power for the test-duration, and fatigue index (based on a ratio of peak and average power) are measured [167]. The use of a laboratory test allows easy measurement of blood, expired gases, muscle biopsy, electromyography, and most recently proton magnetic resonance spectroscopy [169].

It is assumed, the phosphagen system energy supply exercise duration is under 20-s [170]. Post exercise lactate levels for durations as short as 10-s, indicate there is a significant glycolytic contribution to very short sprints [171], and lactate continues to increase from both 10-s and 20-s maximal exercise, demonstrating a growing glycolytic contribution [172]. Invasive measures of aerobic metabolism indicate supply was 28% aerobic for 30-s, 49% for 60-s, and 64% for 90-s [173]. Comparing the first half of a 30-s maximal effort suggested a predominance of phosphocreatine supply with a shift towards aerobic supply in the second half of a 30-s test [174]. Aerobic supply for 30-s power was 40% (28% in the study above showing variation between studies), and for 60-s increased to 50% in cyclists [175]. While aerobic contribution for 10-s was 3%, after 30-s the aerobic contribution rose to 28%, and to 46% for a 90-s cycling test reflecting glycogen depletion [176]. Similar percentages were observed in junior cyclists performing a 10-s sprint [177].

Similar observations on the aerobic system involvement were made in other sports. Aerobic contributions were observed in 200-1500-m running events [178], and 100-200 metre running events [179], Olympic 200-m kayak events [180, 181], and 100-m swimming events [182]. These data strongly suggest aerobic energy supply is substantial for typical sustained sprint events. Speed curves from the first sections of the 100-m running event showed a 6% aerobic contribution to performance [183]. These similarities in energy supply in cyclists and other sprint athletes are useful to guide cyclists towards events suiting their physiology, training to maximize ability and optimise racing performance.

2.4.2 Application of the science to the flying 200-m

Maximal power relative to frontal area and optimizing pedal frequency lead to the best performance in the flying 200-m (f200) used to seed riders at the start of a sprint competition [184]. The approach leading into the f200 also requires planning to ensure optimal pacing before the rider hits the 200-m mark, and timing starts [166]. Fig. 2.2 illustrates the power output of a 16-yo female cyclist performing an f200 on the velodrome, with an overall parabolic shape to illustrate the f200-m process.

The rider enters the track with 3.5 laps to ride and progressively gains height on the banking, to jump from the highest point to use the banking to gain speed before the timing of the 200-m commences. In contrast, Fig. 2.3 shows the same rider performing a 3-lap sprint race where the first two laps are at low speed and power as riders employ tactics to gain a favorable position and aim to jump before the other rider. These figures clearly show how power varies and how high power and peak power are held for some seconds after an initial commencement, rather than a single all-out effort, which again challenges the use of PPO in predicting or training for sprint performance.

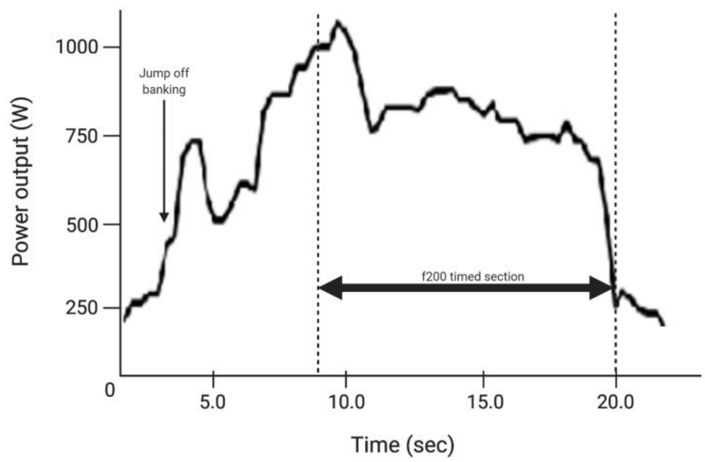

Fig. 2.2: Power output for f200 by 16-yo female

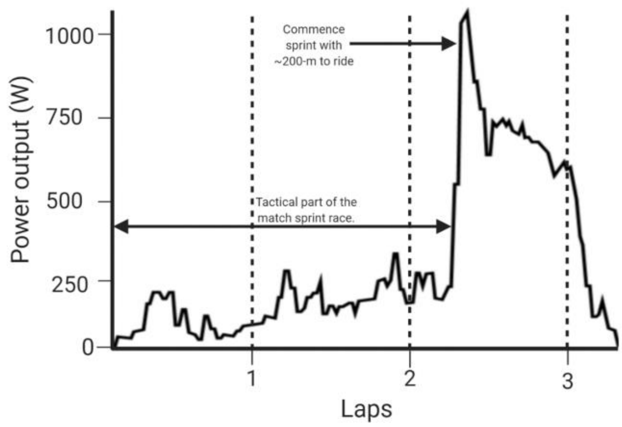

Fig. 2.3: Power output for a 3-lap match sprint race by 16-yo female

Even near the initial 15-s, power output over 15-60s is not a function of phosphocreatine supply. Glycolytic supply is highly involved, first through oxygen-independent pathways and then, especially past 30-s, oxidative pathways. While these measures are clear in the laboratory, these assessments do not account for the demands of the sport outlined in Section 2.2.

2.4.3 Summary:

The primary takeaway points from this section are:

- Sprint events require 15-60s power durations, which in turn require both anaerobic and aerobic energy pathways.
- Power requirements in a sprint event are not peak power focused, as currently trained, but variable, including an endurance element.
- There is dearth of data on sprint event power upon which to draw conclusions directly, although there are limited simulation studies.

2.5. Multiple Sprint Performance

While ample literature covers the power demands of road cycling [185-189], data are lacking for sprint-cycling events. As described, the focus of testing has been on one-off performances in the field, or on an ergometer for durations of 30-s or less. One-off tests create a gap in the understanding the competition demands and individual abilities of the sprint-cyclist to deliver power over a sprint-competition. However, there have been studies of repeated sprint ability (RSA), like sprint-competition to inform decisions on sprint-cyclist preparation.

No formal test of multiple sprint racing is utilized in sprint cycling. A potential model is based on critical power [190]. Critical power (CP) is based on several trials measuring power over various durations, plotting each point to determine the asymptote, to demarcate the transition from the heavy work domain and the severe work domain [190-192]. The curvature constant of the power duration curve provides a measure of high intensity capacity, called *W'* [193]. The balance of *W'* (*W'*bal) has been modelled, estimating the depletion when exercising above CP, and reconstitution when riding below [194-196]. Such a model could potentially predict performance over a series of sprint races. However, there are several challenges to the *W'*bal concept [197-202].

A study comparing recovery from 3 x 30-s cycling tests, showed subjects with a high proportion of type I muscle fibers recovered within 20-min. However, subjects with a high proportion of type II fibers still showed fatigue after 5-hrs [203]. Recovery from short term intense exercise was related to capillary size, larger size facilitating blood lactate clearance [204]. After a 30-s maximal sprint, phosphocreatine levels took longer to recover than previously observed [205]. After 30-s of maximal effort, greater utilization of phosphocreatine in type II fibers was observed, leading to reduced performance in a subsequent test, while after 4-min recovery, type I phosphocreatine levels restored to baseline [206]. There is a strong relationship between aerobic fitness and recovery from high intensity intermittent exercise [207]. Thus, most sprint-cycling competitions do not permit full recovery, increasing requirements for aerobic energy pathways to contribute (further) to sprint racing performance.

An investigation of performance and physiology for a 4 x 30-s test with a 4-min recovery showed muscle glycogen was depleted and aerobic supply was involved for the final repetitions, including even intramuscular triacylglycerol stores [208]. Another study of 3 x 30-s sprints with 4-min recovery, showed depletion of glycogen by the final repetition [209], while a similar study, focusing on phosphocreatine, showed by a third repetition, aerobic metabolism was the primary source of energy supply [210]. In a comparison of repeated 10-s and 20-s sprints, data show peak-power could be reproduced, but average power could not be maintained after 120-s recovery [211]. While phosphocreatine stores recovered, the drop in average power in repeated sprints was associated with reduced glycolytic energy supply [211]. After repeated sprints, force generation was compromised for over 20-min [212].

In a Keirin simulation using four 30-s Wingate tests over a 10-hour period, with 1-hour between trials 1-2, 4-6 hours between rides 2-3, and a further 1-hour between rides 3-4, there was a decrement in performance in untrained participants between trials 1-2 and 3-4 suggesting an hour was insufficient for full recovery [213]. All sprint events feature rounds, with short turnarounds, which highlights the need to focus, not only on power delivery in sprint cycling, but also capacity and recoverability. In a simulation of BMX competition comprising 6 x 30-s Wingate Tests with 30-min recovery, both anaerobic and aerobic supply contributed to all six repetitions, and in the third to sixth race simulation, acid-base balance was altered showing a lack of recovery between the final repetitions [214]. Thus, the force-velocity profile of single vs. multiple sprints highlights the need to assess sprint performance specific to the demands of the event [215]. The rider must balance racing in each round, with performance over the entire sprint series.

After a simulation of the sprint event, with f200-m and four match sprints, the muscular properties in the lower limbs related with fatigue over the tests [216]. Recovery from a 30-s sprint was a process of balancing potentiation and suppressing fatigue [217]. Because RSA tests show consistent large decrements in force production and technical ability [218], it is important to view track sprinting in its competitive context and beyond a singular challenge, and thus to avoid training to single effort test results.

Given the aerobic contribution to sprint events, it does not make sense to predict performance with commonly used one-off tests of 4-30 second power [219]. RSA was shown to have an influence on one-off sprint performance, as well as, obviously, repeated sprinting [220]. The aerobic contribution also implies a need for training to build capacity for repeated sprints, and multiple events, not covered by targeting single-effort and peak-power measures. Training the aerobic energy system in sprint cyclists is different to the approach described about New Zealand sprint athletes leading into the London Olympics, who followed a very low volume, maximal intensity program [219]. While testing in 4-s power showed improvement towards the Olympics, performance at the 2012 Games was lower than expected.

The leading predictor for RSA appears to be maximal sprint speed [54, 221]. However, research is lacking on an association between sprint speed and sprint-competition performance, in the same way there is no association between PPO and racing outcomes, perhaps due in part to the association between aerobic capacity and recovery during RSA. The aerobic system is involved in recovery between sprints, and is likely associated with restoration rate of phosphocreatine stores [222]. Recovery duration and the pattern of spacing restoration (constant, increasing, and decreasing recovery length) also significantly influenced RSA [223, 224]. Despite the evidence for an aerobic contribution to sprint performances, and evidence showing the importance of recovery capacity between performances, there is a strong reluctance to include aerobic training in preparing sprint athletes. Nevertheless, competition demands demonstrate the repeated nature of sprint-competition, stressing both the capacity to deliver power via multiple pathways, and the importance of recovery between races, within an event, and between events. Thus, single power metrics, especially single sprint measures, to make training, selection and competition decisions are obsolete at best.

2.5.1 Summary:

The primary takeaway points from this section are:

- There are currently no standard methods for assessing repeated sprint ability.
- Repeated sprint ability is influenced by quality of the oxidative energetic system, thus performance testing must implicate the oxidative pathways.
- Training for events requiring repeated sprinting should optimize the oxidative pathways.

2.6. Optimizing Track Cycling Sprint Cycling

Optimizing performance in sprint-cycling involves minimizing the [external] demands of riding while maximizing the [output] supply of the athlete by augmenting the mechanical and physiological efficiency. Unlike the volumes of research on training for endurance cycling, there is a paucity of research focusing on either the specific demands of track sprint-cycling events, or the energy supply required in competition. Thus, coaches must rely on general knowledge to make decisions on coaching track sprint-cycling events.

2.6.1 Aerobic Training for Sprint Athletes

A recent review on improving sprint-performance across numerous sports suggested a lack of both descriptive and investigative studies on sprint performance [225]. Most suggestions made, were of the *best practices* of well-performed sprint coaches. Curiously, there was no mention in the review on the use of training of the aerobic system, whether to enhance recovery or, for cycling, reflecting the aerobic content of even a 10-s sprint mentioned in Section 2.2. The contribution to longer sprints mentioned in Section 2.3, the variability in power produced and required (per Fig. 2.2), or repeated sprint performance from Section 2.4, were also not mentioned. An earlier review comparing recovery from high intensity exercise suggested aerobic fitness assists in ATP-phosphocreatine recovery and improved clearance of lactate [207]. Hence, training to meet the well-defined need for capacity in sprint-cycling events is unmet.

2.6.2 Competition

In an observational analysis of the New Zealand sprint cycling team preparing for the 2012 Olympics, there was a marked distinction between maximal power measures from on-bike power meters, from peak-power to 30-s power, compared with PPO from inertial testing [219]. While PPO from inertial testing was highest in the lead-in to the pinnacle event, power meter wattage dropped substantially, and this drop was reflected in performances below expectations [219]. This data, albeit from a group of five male and three female riders, of which only three male, and one female, competed at the Olympics (due to entry criteria), suggests a focus on PPO in an inertial test was lacking specificity compared to all of the demands of competition.

2.6.2.1 Tactics

A study of f200 performance and overall rankings of World level match sprint events suggested better performance in seeding was predictive of overall placing [226]. Outside of qualifying times and overall rankings, no further data has been presented for sprint races (match sprint and Keirin). The varying nature of each sprint race ensures power and speed data have negligible impact.

2.6.2.2 Pacing

An all-out approach is coached in most sprint events [227-229]. However, in the literature, the definition of all-out is not starting maximally and trying to withstand fatigue, more to start fast to achieve a speed sustainable over the distance [229]. In the time-trial or team sprint, the standing start does influence pacing [230]. Application of the Brachistochrone problem in physics to the f200, describes the optimal line from the top of the banking, down to the measurement line of the track [166]. In this approach, suggestions were made on optimal speed coming into the start of the sprint, and description of the physics of riding in the bends, higher speed and lower power, and the inverse riding along the straights of the velodrome [166].

In a comparison of a 30-s test ridden “all out” or paced, there was no difference between approaches, and in a time trial in contrast, pacing affects performance [231]. However, in a mass start race a rider adopting an all-out approach would slow down over the ride, and any trailing riders would receive an aerodynamic advantage by drafting [231]. Comparing a 10-s with a 30-s Wingate test suggested the longer test gave a better understanding of anaerobic capacity [232]. Overall, across these studies, a focus on PPO did not improve short term work capacity in a 30-s test [233].

While none of these studies are based on competition data, the underlying physiology suggests pacing over the entire distance. This pacing suggestion holds even when competing in sprint events, where current coaching practice focuses strictly on PPO and excludes any concept of pacing or endurance [228, 229, 234]. The outcome of these studies provides the coach with a sound basis for giving pacing advice to riders based on sound physiology, as well as to considering training multiple energy pathways.

2.6.3 Summary

The primary takeaway points from this section are:

- Track sprinting is likely enhanced by greater oxidative system training. However, more research is needed on optimal levels.
- Research is lacking on specific strategies to optimise tracking sprinting within competition.

2.7 Recommendations and Conclusions for sprint cycling

The overall outcome of this review shows specific need to consider a much wider range of power metrics when assessing riders. When performance results are linked to specific power measures, such as 30-sec power for the sprint events, they miss critical elements needed to perform well in competition, and thus have so far failed to predict performance results accurately or consistently.

In particular, the review finds gaps suggesting further research is warranted in:

- The primary test of sprint performance is a one-off test of 4-30 seconds, and the current model of sprinting is based around neuromuscular power and phosphagen energetic pathways. While PPO, and its associated measures are an important part of sprinting it does not provide a full picture of sprint cycling competition.

- The physiology clearly shows there is a glycolytic and most importantly an oxidative contribution to sprint performance, even as short as 10-s. Research is needed to further elucidate these differences to ensure coaching reflects an accurate physiological model.

- All sprint track cycling events involve repeated sprint activity. The physiology clearly shows sprinters with a high proportion of type IIx fibers recover slowly from maximal efforts, and an increasing contribution of oxidative energy supply as the number of repeated sprints increases.

With such clear evidence for the oxidative role in sprinting, and repeated sprint activity, research is needed to determine the optimal balance of neuromuscular training, and balance of different types of training to optimise phosphagen, glycolytic and oxidative energy pathways relative to actual competition.

Understanding the oxidative energetic supply in sprint cycling would help optimize training methods, thereby improving performance. Understanding oxidative energy supply in sprinters would close the gap on what is still, more art than science, in coaching. Fig. 2.4 summarizes the review by proposing the development of cycling specific tests reflecting the capacity and recoverability demands of track cycling events to provide a better overview and target for rider training compared to an increasingly single metric per event focused coaching approach used today in several parts of the world.

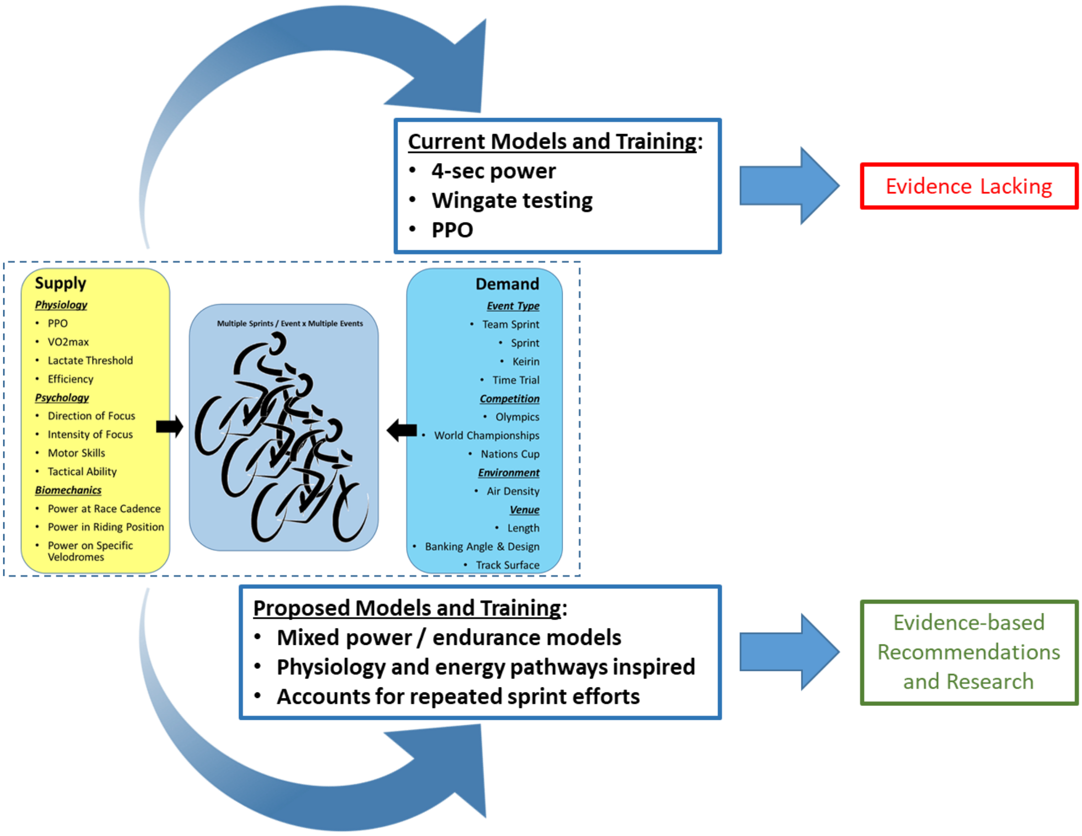

Fig. 2.4: Current and Proposed models of measuring performance in track cycling based on the review of supply and demand power in track sprint cycling in Fig. 2.1.

Building on the physiological data from measurement of sprinting and repeated sprint exercise, models are proposed based on field testing of sprint competitors. The use of regression models to ascertain relationships between power for various durations and derived metrics and competition times and results. The development of field-based tests considers the repeated sprint nature of track cycling competition. New models should provide a clearer picture of sprint competition performance and allow for a more comprehensive approach to the preparation and coaching of sprint cyclists.

Overall, this chapter highlights the need for a better understanding of the physiological requirements of competitive track cycling. Developing better measures of these aspects would enhance the understanding of competition demands, and therefore lead to better choices being made with regards to testing, training and performance.

2.8 Track Endurance Cycling

Table 2.2 summarizes the World Championship endurance cycling events. World Track Cycling Championships typically take place over five days and feature an endurance race and a sprint race each day. Some events may take place over 2 days. Olympic Championships schedules are typically dictated by television schedules so may be subject to different formats.

Pursuit cycling is performed in the extreme and severe exercise intensity and duration domains [235]. Lactate threshold is the transition from heavy domain to severe domain and is commonly assessed by performing a ramp test to exhaustion taking lactate samples and using various methods to determine threshold [236, 237]. These tests are all dependent on the protocol used to determine transition power and should not be used interchangeably [238-240].

Table 2.2: World Championship Pursuit Events

Event	Description	Race Format
Team Pursuit*	Teams of 4 riders race over 4000-m with the aim of catching their opposite team or record the fastest time for the distance.	N = 3 rides in 2-3 session in 2 days • Qualifying round • Round 1 • Final: Gold and Bronze Medals
Individual Pursuit	Elite Male riders compete over 4000-m and Women over 3000-m, with the aim of catching their opponent or record the fastest time for the distance. From 2025 Women will compete over 4000-m.	N = 2 rides in 2 sessions over 1 day
Points Race	Riders compete over a set distance, and score points in intermediate sprints (5,3,2,1, points, double on last lap), or by gaining a lap on the field (20 points, and -20 for losing a lap on the bunch).	N = 2 (if heats are required to bring make the field size no more than 24 on 250-m track).
Madison*	Two person teams' race, where one rider takes a turn then exchanges with his teammate. Race is run in points race format.	N = 2 (if heats are required to make the field limit of 18 teams)
Scratch Race	Raced over a set distance and first rider to complete the distance is the winner.	N = 2 (if heats required)
Elimination Race	Every 2nd lap the last rider in the race at the finish line is eliminated until there is one rider left.	N = 2 (scratch race heats if required)
Omnium*	4 race event: Scratch Race, Tempo Race (variation of the points), Elimination Race and Points Race where riders score points in each event and the winner is the person with most points.	N = 5 (4, unless points race heats if required)

* = Olympic Event

Mathematical models estimate the threshold between the heavy and severe exercise domains [241]. Power meter estimates of the lactate threshold are referred to as the function threshold power (FTP). While, FTP and CP measures are practical, there is much confusion over numerous protocols, and how these measures should be used to estimate the transition from heavy to severe domains of exercise [239, 242, 243]. While the transition point can be used as a measure of fitness, which can be trained, CP is often used in practice to anchor training intensities. CP may be practical for training in the heavy domain. However, with a large variation in power between riders in the severe and extreme zones, data has yet to be presented predicting high-intensity training zones using CP.

High intensity energy (*W'*) has also been modelled and its depletion and reconstitution are referred to as *W'*bal [194, 244]. $\dot{V}0_2$ kinetics during variable exercise showed a relationship with critical power and *W'*bal models [245]. However, other studies failed to adequately model actual performance due to failing to accurately account for recovery from high intensity activity or accounting for changes in gross efficiency with rising fatigue [197, 199, 200, 246-248]. Prior exhaustive work influences *W'* reconstitution [247, 248]. Power while recovering between exercise bouts is more predictive of *W'* recovery than the duration between events [199, 200]. Mulder et al. [246] suggest correcting for gross efficiency when quantifying anaerobic work capacity. Clearly, the complex physiology of exercising in the severe and extreme domains is not easily modelled with varying energy reserves, handling of waste products are either removed or recycled, and the individual nature of an athlete between and within bouts [249, 250].

The complexity of the underlying physiology has led to model development to understand endurance track cycling performance based on energy systems, the power duration curve, and various physiological landmarks [251, 252]. However, Zignoli et al. [253] warn current models used in cycling fail to encapsulate the complex underlying physiology. The use of bicycle-based power meters allows coaches to measure field performance more objectively, while laboratory testing focuses on physiological transition points.

There are several studies on the power required to perform in road cycling [186-188, 254-256]. However, there is nothing describing the power required for the Olympic track endurance events beyond one-off rides [47]. Schumacher and Mueller [65] described the anatomical and physiological traits of the German team preparing for the 2000 Olympic team pursuit, where the athletes were characterized by height, high $\dot{V}0_{2PEAK}$, high maximum lactate levels, and high power in a 4000-m individual-pursuit. With a lack of studies on the physiological basis of track endurance events, coaches must rely on data from related sports and physiological interventions.

2.9 Optimizing endurance track cycling performance with power meter data

Optimizing performance in track cycling essentially involves finding ways to minimize the demand of riding, maximizing the supply of energy of the athlete and becoming both more mechanically and physiologically efficient. While huge volumes of research on training and nutrition have been performed, there is no research focusing on the specific demands of track cycling events nor the energy supply required. Thus, coaches and athletes must rely on general knowledge to make specific decisions on preparation and competition in track cycling events. Castronovo et al. [124], proposed a model for optimizing cycling performance based on targeting both metabolic and mechanical efficiency. However, optimization is limited by the anthropometric, biological, and hard to quantify psychological potential of the rider [47, 257].

Numerous sports evaluate event demands and corresponding tests of athletic ability. However, apart from brief overviews of team preparation [65, 219], there is no comprehensive evaluation or framework of the specific demands of track cycling. This lack of framework for track endurance cycling has led to a situation where athlete assessment is based on general measures, like the Wingate test for sprinters, or lactate threshold test for endurance cyclists [258]. Thus, a lack of information, like what is found in sprint cyclists, is also found in the severe and extreme exercise domains.

Approaches to optimizing track cycling performance follow a biomechanical approach of improving the bike-rider interface through using supply-demand models and testing various inputs to discover areas of improvement [259]. There are numerous investigations of performance in cycling at a given moment, summarized in van Ingen Schenau et al., Kautz and Zignoli [228, 260, 261], or parts of the performance, like a standing start or the power for a given position of a team pursuit [64, 262], there is no research on the events as a whole.

2.9.1 Optimization: Rider assessment, event selection and training

2.9.1.1 Rider assessment and event selection

A power meter can be used to measure efforts from testing, training, and competition, offering the benefit of specificity. In the laboratory, the Wingate Test measures peak power, time to peak power, average power, and fatigue index (peak: average power ratio). Wingate test data can be used to understand sprint performance energy supply [167, 263, 264]. The anaerobic speed reserve (ASR) in running is based on a model incorporating peak running-speed, and peak aerobic running-speed (speed at $\dot{V}0_{2max}$) [265]. ASR has been adapted for cycling using 3-s average power and power at $\dot{V}0_{2max}$ to predict performance in events from 5-s to ~300-s [266, 267]. Of the two durations providing input to the model, the duration closer to the time being predicted had the strongest relationship with results [268]. ASR has also been used in swimming events to assess recoverability [269].

The $\dot{V}O_{2max}$, obtained from a progressive ramp test to exhaustion is still the most commonly used test of aerobic fitness [168, 258]. In cycling, the power at $\dot{V}O_{2max}$ is referred to as maximum aerobic power (MAP) [270, 271]. The format of the ramp test can affect the measures recorded in a $\dot{V}O_{2peak}$ test [238, 272, 273], introducing variability in the results. Testing MAP removes the need for measuring expired gases and can be performed in the field [270, 274]. Similar to sprinting, measures of power over different durations, such as the critical power (CP), are used to predict performance in endurance events, and estimate high intensity energy (W') [190, 199, 275, 276]. In a comparison of several models estimating $\dot{V}O_{2max}$ from power meter data, the models by Olds et al. [277] and McCole et al. [278] predicted $\dot{V}O_{2max}$ well with velodrome and laboratory ergometer tests [279]. Maximal lactate steady state was estimated from 5-km and 40-km TT tests [280].

Methods attempting to define the maximal fractional utilization of $\dot{V}O_{2max}$ [241], include the lactate threshold [281], the maximum lactate steady state, respiratory compensation threshold/point, or critical power [239, 282]. Lack of specificity in these tests, accuracy representing target phenomena, and poor reproducibility relative to the smallest-important performance effect size raise questions about their validity [283].

2.9.1.2 Training

The key to training for any event is understanding the demands of racing for a given level of competition, type of velodrome, event rules and format, and environmental conditions on the day, in the context of the current physiological, biomechanical, and psychological attributes of the rider. Within the given period to the competition, a rider will train and practice to meet the competition demands. A major challenge in track cycling is current models of performance are limited to an event at a given moment, or a single race. However, track cycling, in all Olympic events in their current format, require multiple performances within an event, and between events. While riders can be substituted between rounds in the timed events, the mass start events require performance in all races across an event and recoverability between rounds.

Taha and Thomas [284] review models of the relationship between training and performance, highlighting most models do not match the underlying physiology of performance. For road cycling, recording max mean power values is used to identify the rider profile of different phenotypes, such as (road) sprinter, time triallist, puncher (good at short climbs), and climber [271, 285]. A similar profile could be used in track cycling to identify the best event for a rider, suggest tactics matching a rider's strengths, and guide training decisions.

The challenge of trying to increase power through training or reduce the need for power by optimizing the bike-rider interface, is there is only a limited progress to be made, and all elite athletes receive similar inputs. An alternative approach is to focus on the capacity at a given level, knowledge of the power for a given duration from sprints to longer track events, and instead of trying to increase the power for these durations, to try and hold power longer periods and/or repetitions. A focus on capacity, and by extension recoverability, could be more productive through compliance with one of the main tenets of fitness: the principle of progressive overload [286].

2.9.2 Competition

2.9.2.1 Warm Up

A power meter can be used to assess the warmup. First, to ensure the rider is sufficiently prepared to race. Second, to ensure the rider does not warm up too much detracting from their energy to devote to the event itself. To enhance performance a rider should perform a short but near maximal effort as part of the warmup [33, 287]. A new area of research is post activation potentiation (PAP) where doing a maximal effort, either using the bike, barbell, or bands, as part of the warmup, has a positive effect on performance [219, 288, 289]. A working model of high intensity energy, like the *W'*bal model [244], would have potential to indicate if these warm up efforts were sufficient to potentiate the rider, yet ensure they had sufficient energy to perform once racing.

2.9.2.2 Starts

A power meter can be used to assess the start. Optimization of the start is delivering enough power to get up to race speed for the distance, balanced against not expending too much energy for the rest of the race. Power, cadence, and crank-torque demands of seated start were modelled. However, the standing start model needs to incorporate the upper body, as all starts in track cycling are performed out of the saddle [290]. Different muscle activation was identified between the first 125-m of a standing time trial and the second 125-m where the rider would transition from out of the saddle to in the saddle [8].

2.9.2.3 Pacing

In the track endurance events, pacing is a key area of opportunity for optimizing performance. Table 2.3 summarizes the numerous studies in the area. Key findings suggest starting fast up to the goal speed for the event and holding an even pace.

Table 2.3: Summary of studies on pacing in the individual pursuit

Distance	Authors	Findings
4000-m	Ansley et al. [83]	Pacing in successive efforts were centrally regulated.
	Hettinga et al. [291]	Peripheral fatigue was more prominent than central down-regulation.
	Stone et al. [292]	Lab simulation is a reliable test to monitor performance and pacing.
	Mauger, Jones & Williams [293]	Riders with a lack of feedback or knowledge of distance learned to be competitive over successive efforts.
	Mauger, Jones & Williams [294]	Performance feedback is advantageous.
1500-m – 2000-m	Foster et al. [30]	Rider's conserve anaerobic energy supply, not a large learning effect, anaerobic energy a discriminating factor in performance.
	Hettinga et al. [295]	No difference in aerobic/anaerobic supply for all pacing strategies.
	Corbett, Barwood & Parkhouse [296]	Over successive trials pacing was adjusted to start slower on each successive effort.
	Hettinga et al. [297]	Participants varied their pacing on a given day depending on their mean power output.
1000-m and 4000-m	de Koning, Bobbert and Foster [82]	Best results obtained for 1000-m from all out start and 4000-m for first 12-s then averaging pace of whole ride.
Time based	Aisbett et al. [298]	Fast start in a 5-min performance was optimal.
	Bailey et al. [299]	In a 3-min and 6-min test a fast start strategy improved 3-min power

Research on pacing, not only in cycling, but skating and rowing, over distances of 1.5 – 4 km gives insight into physiological abilities required to perform in endurance events. Power output and integrated electromyography data from a 4000-m cycling simulation showed a relationship with peripheral fatigue [291]. In this study, subjects performed a fast, even-paced, or slow first 2000-m and completed the second half as fast as possible. Only the slow start led to increased power in the second half, while even-paced and fast starts led to less power [291]. However, a fast start to a 3-min test led to a better overall performance due to improved $\dot{V}0_2$ kinetics [299]. An all-out start was optimal for both the 1000-m and 4000-m simulations. However, for the 4-km distance, the optimal performance occurred when, after 12-s, the rider paced the rest of the ride [82].

2.9.2.4 Reducing Drag

To counter the expense of wind tunnel testing, models of estimating drag based on power meter data have been used to determine drag [300, 301]. Drag data can be compared against power delivered. More aerodynamic riding positions can lead to a reduction of power production, and a balance should be found between aerodynamics and speed [137, 138, 302]. The drag data can be used to optimise the position of riders in team pursuit [301, 303, 304].

2.9.2.5 Tactics

In the timed events the main tactical consideration is pacing of the ride. The coach can give feedback to the rider by calling lap splits, showing a PDA with lap splits, or by standing up or down the track to indicate whether a rider is up or down on a schedule or against an opponent. Unlike road cycling competition, track cyclists are not allowed to view a computer while riding, use radios when competing as occurs in World Tour level road cycling.

Mass-start events are complicated by the dynamics of bunch racing. As explained in the description of team pursuit power, the lead rider needs to generate higher power than those positioned behind them. However, extra energy must be expended to be better placed for the final lap or sprint laps where the races are decided. The variability of competition increases the challenge of optimizing performance. With a clearer understanding of the demands of competition, in particular the capacity required to perform between rounds an event, and between an event the coach can make better decisions of optimizing performance.

2.10 Summary of Endurance Track Cycling

Track cycling requires a mix of speed and capacity. While events are between 2:15-min – 4:45-min long, riders typically perform a large volume of training in proportion to the race distance. Differences between sprint and endurance track cycling reflect muscle fiber typology with some crossover between events like the kilometer time trial and the pursuit. Despite phenotypical differences between riders, there is a commonality between the two in terms of training for the capacity to compete in their given events and maximizing their maximize their performance in their given event/s.

2.11 Overall Recommendations and Conclusions for Track Cycling

Track cycling, like any high intensity sport taking place between 1-s – 5-min, involves a constant interplay of energetic demands, biomechanical challenges, and psychological requirements. While the physiological demands can be determined in the laboratory, or the biomechanical challenges mapped out, they do not relate perfectly to what occurs in the field. The gap in information is where the advent of power meters has allowed a better understanding, in which measurement of power up to a resolution of every 10th of a second, although typically 1-s recording, can provide real time assessment of performance. The power meter allows for the modelling of track cycling performance, and this thesis examines current models and proposes a new model offering a better understanding of performance.

While performance results are associated with specific power measures, such as mean 30-sec power for sprint, and 3-min mean power for endurance events, these measures miss critical elements of power demand-supply dynamics. Hence, they fail to adequately predict performance. As presented in this chapter, further research is warranted in:

- The evaluation of models of testing training and assessing performance using relative measures of power over absolute metrics.
- The capacity to sustain power at high intensities over several rounds of competition, and between different events, and its role in delivering improved results, as well as specific power, in sprint and endurance events.
- The recoverability, and measurement of recovery time and quality between event performances, particularly when major events have multiple rounds and rider compete in multiple events. Potentially through development of the ASR and *W'*bal models.

Closing these gaps would enable better informed training methods, and potentially improved results, reducing what is still more coaching by art than sport science. Fig. 2.5 summarizes the review in this chapter, as well as prefacing part of this thesis, by proposing the development of cycling specific tests reflecting the capacity and recoverability demands of track cycling endurance events.

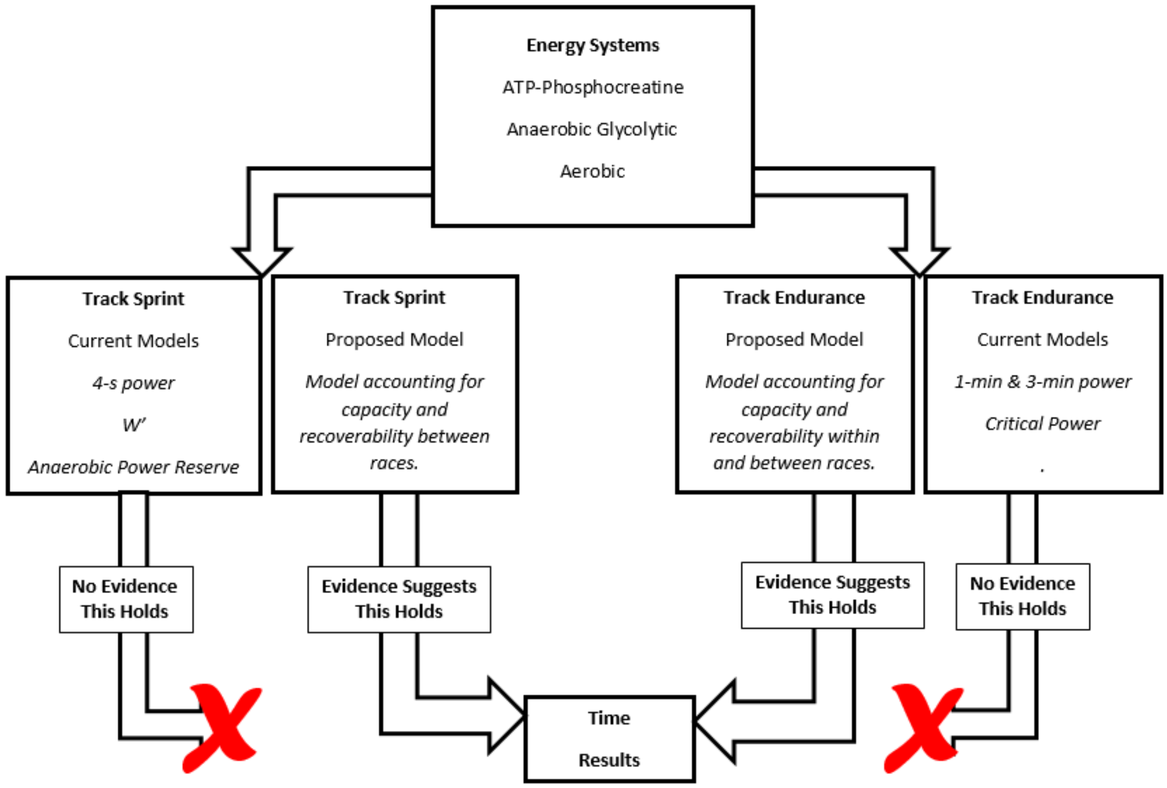

Fig. 2.5: Current and Proposed models of measuring performance in track cycling.

Chapter 3: Modelling 30-s sprint cycling performance: Assessing the aerobic contribution

Data presented within this chapter has published in:

H. A. Ferguson, T. Zhou, C. Harnish and J. G. Chase, **Model of 30-s sprint cycling performance: Don't forget the aerobic contribution!** IFAC-PapersOnLine 2021 Vol. 54 Issue 15 Pages 316-321

3.1 Introduction

Current practice in coaching track cycling sprint athletes focuses on a very narrow band of power output from 1-4 seconds. However, there is an oxidative contribution, even to sprints as short as 10-s. This contribution increases as a rider competes in multiple events, where it is important to note all Olympic and World Championship level international, and many national, track cycling events require repeated heats and performance.

This chapter analyzes sprint-cycling performance to investigate the role of durations requiring a high oxidative contribution to energy supply and their relationship to sprint-cycling power durations. This comparison aims to show sprint cyclists require a measurable level of endurance power at sub-elite and elite levels. In particular, it hypothesizes power at endurance durations are strongly related to power at sprint durations. Further, it hypothesizes these relationships may be nonlinear and potentially saturable.

The maximum mean power represents the maximum power an athlete can sustain for a given duration [305], and is used regularly as a training tool for competitive cyclists [265]. Various models exist to populate the curve with maximal efforts at various durations, and the best of these models test durations from 1-5 seconds, 30-60 seconds, 3-8-mins, and greater than 15-mins [193, 305]. Models are used to fill in the gaps between true maximal efforts. The power duration curve can be used to determine areas where more testing is needed, or to ascertain strengths to be maintained and weakness to be trained [306, 307].

Once a well-developed power duration curve is established for a rider, it can be used to guide an athlete towards events where they have the best chance of success, and to guide their tactics in racing, in particular pacing, and especially in events with a stochastic nature [194, 307]. However, to date, such curves require specialized tests and models, where suitable tests interrupt training too much and thus, cannot be monitored regularly enough to optimise coaching. The use of power meters and easily obtained data could, with the right model, make the process far more streamlined and it would be based of field data, so might better represent rider capability than one-off maximal tests.

Current thinking among sprint cycling coaches, based on my experience of coaching sprint cyclists to Olympic level, holds power for sprint events is supplied mainly by the phosphocreatine system, to a lesser extent, non-oxidative glycolytic pathways, with limited contribution from oxidative pathway although no research using power meter data, nor physiological estimates has been applied to sprint cycling competition. However, recent reviews show the belief about sprinting being purely reliant of oxygen independent pathways may not hold [308]. For example, measures of lactate after a 10-s test showed glycolytic processes occur well before phosphagen stores are depleted [171]. Duffield, Dawson and Goodman estimate the energy contribution using lactate measures, and phosphocreatine degradation estimates to 100-m athletics sprinting, suggesting a 8.9 (±3.3) % oxidative contribution for males and 10.9 (±5.8) % for females [179]. Therefore, it is clear sprint events utilize all energetic pathways, where the impact of muscle fiber type and relative numbers on performance remains to be elucidated.

For instance, data by Nummela and Rusko [309] indicate when energy release was compared between sprint and endurance runners, there were differences only in the second half of the run, where sprinters relied more, but not solely, on oxygen independent pathways. Considering the approach to testing and training sprint cyclists, this result may reflect more on athlete preparation and the potential of aerobic conditioning.

Based on data showing glycolytic and oxidative contributions to sprint performance, this research used power meter data to determine whether increasingly aerobic dominated power durations have a relationship with performance at sprint duration, and vice versa. They include zero power (0,0) to avoid models indicating the possibility of having sprinting power with zero endurance, or vice versa. Overall, it hypothesizes sprint and endurance power are strongly, and possibly nonlinearly, related, demonstrating the need and potential for endurance training in sprint event preparation. The study uses retrospective data to develop models of sprint cycling performance as a function of anaerobic and aerobic power metrics. The data was supplied to the lead author in his capacity as a coach, sport science consultant, beta tester of power meter analysis software, and researcher by individual cyclists from 2006 to 2020. The model proposed hypothesizes:

A. Aerobic and anaerobic power are strongly related within individual cycling athletes, contrary to current coaching assumptions [171, 173-177, 310]

B. This relationship is nonlinear and saturable indicating a strong inter-relationship with aerobic power exists only up to a certain level, after which returns diminish.

These hypotheses build on the physiological results showing even short sprint duration efforts utilize a range of energy pathways including endurance related oxidative pathways [308]. The first hypothesis would indicate the ability to improve sprinting power and performance via endurance training, linking physiology to performance. The second hypothesis would characterize this response and at what power levels diminishing returns commenced.

3.2 Methods

3.2.1 Participants

A total of 192 datasets from 89 participants, were used on the basis of having at least six months of consistent data, reflecting maximal power efforts for 15-s and 30-s as a performance-based measure of sprint cycling, and 2-min, 8-min, and 20-min. Inclusion criteria was, athletes performing at a national level or international level in either, or both, sprint and endurance track cycling, using a power meter where calibration was possible (SRM, Quarq and Infocrank), and able to provide 3-12 months of consistent data, incorporating training, testing, racing and peak event data. Several participants provided data over several years and each year was added as a separate dataset. This could have potentially biased the results, and reflected performing research during Covid-19, and was weighed against the use of a smaller number of datasets obtained prospectively. Table 3.1 shows the subject data and demographics. All subjects gave informed consent to use their data for the research on the condition it would be anonymized, and thus ethics approval was not sought.

Table 3.1: Participant data included in this study and separated by sprint and endurance riders. Median and interquartile range [IQR].

	M	F	Age (years)	Weight (kg)
All	75	14	29.6 (14.7)	72.2 (9.7)
Male	75		30.5 (15.1)	74.0 (9.1)
Female		14	23.9 (11.1)	60.9 (5.4)
Sprint	15	5	30.2 (17.9)	79.1 (11.4)
Endurance	60	9	29.5 (13.5)	70.0 (7.9)

3.2.2 Procedures

Riders performed training and racing using a bicycle mounted power meter. Power, was measured in 1-s intervals, recorded on a bicycle computer, and uploaded to the online database TrainingPeaks™ (TrainingPeaks, Boulder, CO). Data was synchronized with the sports data analysis software WKO5™ Build 576 (TrainingPeaks, Boulder, CO).

Sprint power was measured as 15-s or 30-s power in W/kg, which is hypothesized to be a nonlinear function of endurance power in W/kg over any one of 2-min, 8-min, and 20-min. Using W/kg normalized power output across sex and overall size. Four functions were used to define the relationship in this study, seeking to find a potential best model, and are described in Table 3.2. In Table 3.2, x is one of W/kg 2-min, W/kg-8min, or W/kg 20-min in Equations (1)-(4), and all other terms (a0, a1, a2, a3, A, h, b) are constant coefficients found by identifying the best function for each case from the measured data. Each function provides a different form or function for a resulting power duration curve.

Table 3.2: Four models proposed with Equation and Model # to the left for easy reference.

(1)	**Exponential**: W/kg 15/30-s = $((h\cdot(1-\exp^{(-A\cdot x)}))$
(2)	**Linear**: W/kg 15/30-s = $(a0\cdot x)$
(3)	**Parabolic**: W/kg 15/30-s = $(a1\cdot x^2+a2\cdot x)$
(4)	**Power Equation**: W/kg 15/30-s = $(a3\cdot x^b)$

Equation (1) was a saturating exponential model, Equation (2) was a linear relationship through the zero power point (0,0), Equation (3) is a parabolic function with a saturating behavior for some sets of coefficients, and Equation (4) is a power law relationship, which also saturates. Each of Equations (1)-(4) start at the point (0,0), a null power point. The 0.0 point acknowledges all energetic pathways are functioning at a given time, and both start at point 0. Equally, Equations (1), (3) and (4) all saturated past highly oxidative power durations, x, depending on the coefficients identified from the data, indicating diminishing to no return in sprinting power for increasing oxidative endurance power past a certain level.

The model coefficients (a0, a1, a2, a3, A, h, b) in Equations (1)-(4) are identified using total least squares [311, 312] because there is test variability and error in both the x (oxidative power over 2-min, 8-min, or 20-min) and y axis (sprint power over 15-s or 30-s) measured power output metrics. Total least squares minimize the perpendicular distance from any point to the line or curve of the formulated Equations (1)-(4) model. The traditional linear model using Equation (2) is included as the simplest possible model and to test the second hypothesis.

3.2.3 Analyses

All models were evaluated in Matlab version R2021a (The MathWorks Natick, MA, USA). Models were identified separately for 15-s power and 30-s power as a function of each of 2-min, 8-min, and 20-min endurance power. Each model was utilized for three different cohorts: all riders together; sprinters alone; and endurance cyclists alone. Each of the nonlinear models (1, 3 & 4) is compared to a standard linear model to assess if added complexity adds model quality, per the second hypothesis.

Model quality was assessed by total least squares correlation coefficient R^2. A higher R^2 value indicated a better model, although small differences may be ignored in favor of model complexity. The 'best model' had the highest R^2 for both 15-s and 30-s power in W/kg across all riders, and either sprint or endurance riders, for which models are identified, and thus was the most consistent for assessing power meter data.

3.3 Results

Fig. 3.1 illustrates models for either 15-s or 30-s W/kg with 2-min, 8-min and 20-min W/kg as the input predictor variable for the exponential (Equation (1)) and linear (Equation (2)) models of Table 3.2, with the other nonlinear models not shown as they are very similar to the Exponential Model. Data from sprint cyclists are presented first for each duration and then combined sprint and endurance cycling data. The line of best fit is shown in each case.

Fig. 3.2 shows all the total least squares Linear Model (Equation (2)) lines from Fig. 3.1 without data points to enable comparison. Table 3.3 shows all high R^2 value results for all models and cohorts, showing how aerobic durations contribute to both sprint durations considered. These results support the primary hypothesis of oxidative energy supply having a strong influence and relationship to sprint ability and power and quantifies these relationships for diverse types of riders. Table 3.3 also shows the Linear Model of Equation (2) is the best model based on the consistently highest R^2 values and minimal model complexity, invalidating the second hypothesis of this chapter, which considered the existence of a saturating effect or relationship, which is only lightly evident in Fig. 3.1.

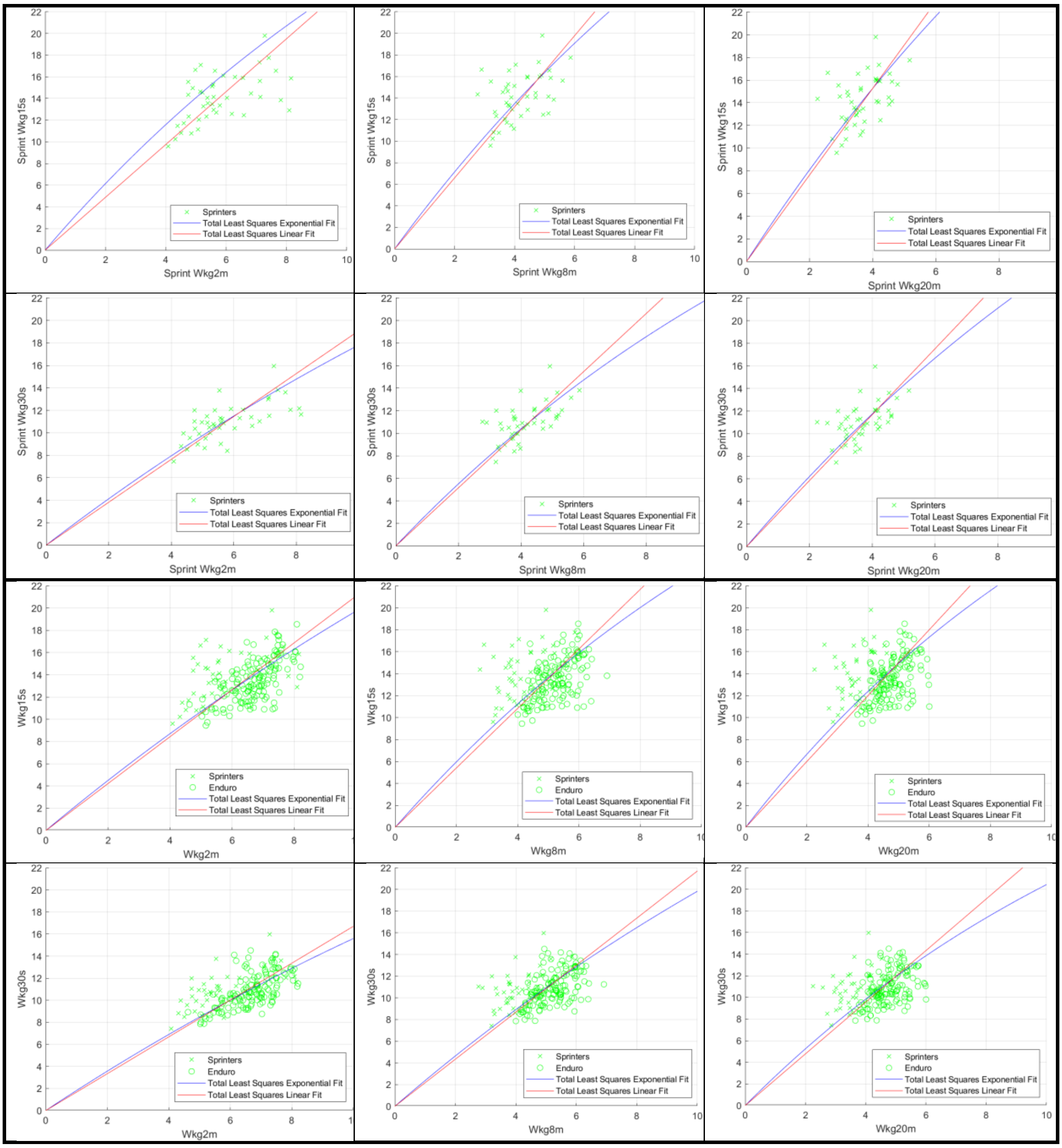

Fig. 3.1: Exponential model (Equation (1)) and Linear (Equation (2)) models for: Row 1: W/kg-15s with Sprinter data only; Row 2: W/kg-30s with Sprinter data only; Row 3: W/kg-15s with all rider data only; Row 4: W/kg-30s with all rider data.

Table 3.3: All models identified and R2 presented.

		Exponential			Linear		Parabolic			Power		
Data	Group	h.	A	R^2	Slope	R^2	a1	a2	R^2	a	b	R^2
30s~20min	All	41.87	0.067	0.80	2.39	0.81	0	2.39	0.81	2.39	1	0.82
30s~8min	All	58.96	0.041	0.81	2.17	0.82	0	2.17	0.82	2.18	1	0.82
30s~2min	All	52.80	0.035	0.82	1.67	0.83	0	1.67	0.83	1.67	1	0.83
15s~20min	All	47.80	0.075	0.84	3.00	0.85	0	2.99	0.85	2.99	1	0.85
15s~8min	All	51.20	0.062	0.83	2.71	0.85	0	2.71	0.85	2.71	1	0.85
15s~2min	All	68.50	0.034	0.83	2.11	0.84	0	2.11	0.85	2.11	1	0.85
30s~20min	Sprint	58.47	0.056	0.88	2.92	0.90	0	2.93	0.90	2.93	1	0.90
30s~8min	Sprint	48.73	0.060	0.88	2.58	0.89	0	2.58	0.89	2.58	1	0.89
30s~2min	Sprint	56.40	0.038	0.86	1.91	0.87	0	1.91	0.87	1.91	1	0.87
15s~20min	Sprint	71.60	0.060	0.92	3.82	0.93	0	3.83	0.93	3.83	1	0.93
15s~8min	Sprint	62.30	0.061	0.90	3.30	0.90	0	3.30	0.90	3.30	1	0.90
15s~2min	Sprint	54.33	0.053	0.86	2.44	0.87	0	2.44	0.87	2.44	1	0.87

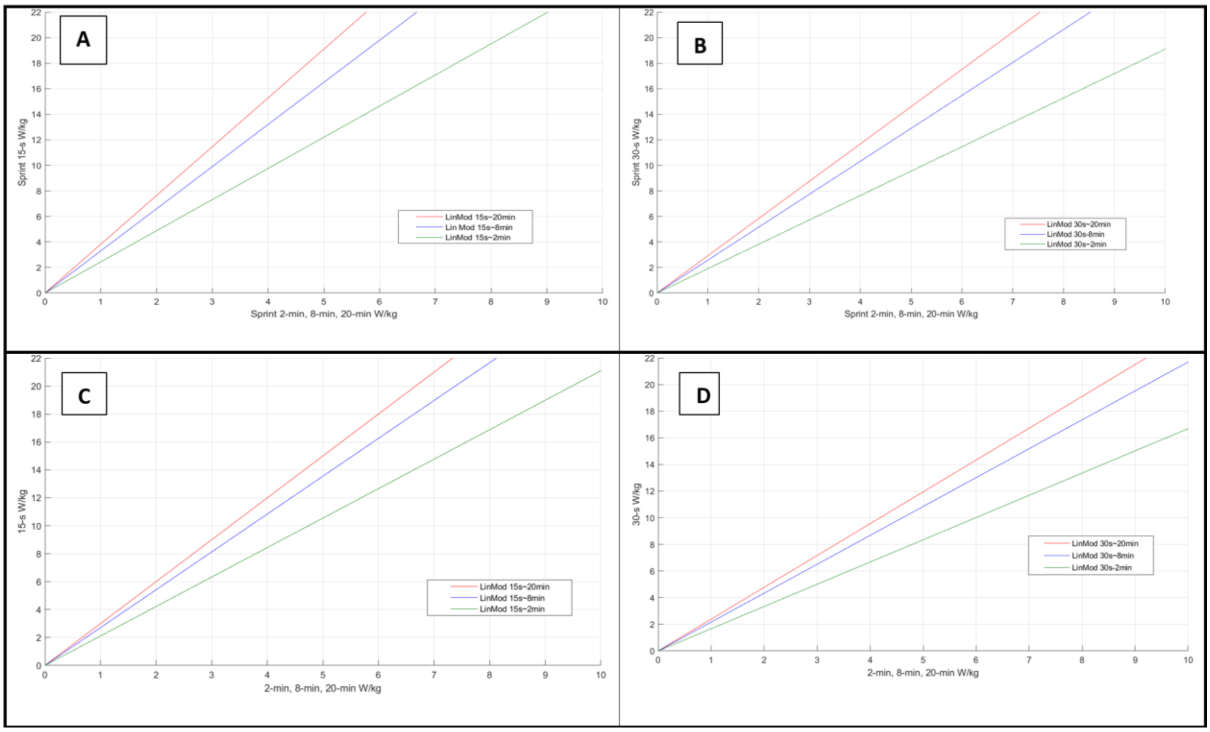

Fig. 3.2: Comparison Plots for Linear model (Equation (2)) results from Fig. 1. In particular, A) Sprint cyclist's 15-s W/kg, for 2-min, 8-min & 20-min W/kg; B) Sprint cyclist's 30-s power; C) All cyclist's 15-s; and D) All cyclists 30-s.

3.4. Discussion

The purpose of this study was to model sprint cycling power as a function of endurance or oxidative driven power. The hypothesis was durations of cycling exercise highly supplied by the oxidative energy system (2-min, 8-min, and 20-min) would relate greatly with cycling exercise durations associated with sprint performance (e.g., 15-s and 30-s). This hypothesis was based on physiological literature [178-182]. However, it is contrary to the current sprint cycling training approaches and framework [219, 225]. These relationships between sprint duration power and oxidative pathway power were hypothesized to be strong, include the null power point (0,0), and to be nonlinear with a saturating or diminishing returns effect at higher power.

Results showed the best model to be a linear relationship between two measures of anaerobic power, and three measures of aerobic power with consistent, strong values of R^2 = 0.81-0.90 across all metrics and cohorts examined. The consistent and strong correlations validate the first hypothesis. The linear model of Equation (2) was best due to equivalent R^2 values but having lower complexity.

Thus, the second hypothesis of a nonlinear saturating behavior was not seen, which is also evident in the small differences between model lines and curves for the Linear and Exponential model coefficients in Fig. 3.1 making them essentially linear, where all other nonlinear models were similar in shape and R^2 (Table 3.3). All these results are further supported by the literature on oxidative and other energy pathway utilization in sprinting events and repeated sprint performance [169, 203].

All models included the point (0,0), the null power point, which precludes other more complex models. This assumption is physiologically appropriate, where a rider could not have a measurable oxygen independent glycolytic watts/kilogram, and an oxidative power of zero, or vice versa. This aspect of the model also highlights the importance of the power-duration curve, which includes low power points, and its potential impact in training riders through long periods of development, where they would move along these lines.

Fig. 3.2 shows differences in slope between the sprint, endurance, and overall cohort. These differences do not invalidate the overall conclusions. The difference in slopes provides a trade-off between effect for different rider types. They are due to differences in phenotype and resulting muscle composition and/or specific training effects. However, the overall relationships are strong in all cases, as in Table 3.3.

3.4.1. Practical Applications

Initial modelling and data suggested a level of saturation where endurance-based power in W/kg would have no further effect on developing anaerobic sprint power, as encapsulated in the second hypothesis. Yet, interestingly, the linear model line suggests athletes sitting below the line should train the y axis or anaerobic power to improve, while athletes above it would benefit more from aerobic oxidative power focused training. The linear model being the best model suggests this trade off would exist at least through the relatively high-power levels included in this data set of elite and sub-elite athletes.

When planning the preparation of sprint cyclists for competition where repeated-sprint performance is required, as in all Olympic level sprint events, the data presented show having a high 2-min, 8-min and 20-min power is positively related to their performance for 15 and 30s power. However, as the data covers periods of 3-12 months, this advice does not mean all durations need to be trained simultaneously. This training could be periodised, so endurance focused training predominates early in the run-in to a major event. For sprint cyclists in particular, where there is a fast drop off of sprint performance due to detraining compared to endurance athletes [313], there is a need for regular sprint exercise to maintain their performance levels [225].

3.4.2. Limitations

The major limitation of this study is the limited datasets of sprint cyclists (N = 20 of 89 total). However, the nature of sprint competition suggests a higher oxidative capacity benefit competing over multiple races and is related to recoverability [203, 314]. Further, and equally importantly, the results for the Sprint cohort alone in Figures 3.1-3.2, and Table 3.3 show strong results, so the relationships and initial hypothesis would hold, even if the exact linear model relationship changed.

A second limitation is the reliance on cross-sectional data from a 6–12-month period including competition and test events. While this choice ensures both a maximal 30-s and 20-min effort, it does not assume they happened at the same time in the training/racing period. However, in terms of estimating the effect of 20-min on 30-s performance it still shows aerobic performance at some stage of the training year is beneficial for the athlete.

3.5 Summary

These results indicate a strong linear relationship and model between 15-30 second power and aerobic power durations from 2-min to 20-min. Even when the data are for sprint cyclists only, the relationships were still strong. A further conclusion is captured by the linear model being the best of all models, indicating no saturation of effect in the elite and sub-elite athletes studied.

This outcome could also be seen to support the idea of training for power over multiple periods, rather than a single-minded approach. Equally, the linear model and its lack of saturation indicates the training implications would not be restricted to specific riders or capability levels, and such periodicity could be used at all levels. The overall result quantifies and builds upon and is supported by physiological research showing oxidative energy pathways play a key role in a lone sprint effort, and repeated sprint effort events.

Sprint cyclists should aim to include some form of aerobic exercise in their program to optimise sprint performance to varying degrees over periods of training, leading to a key event. Coaches can use these results to place specific riders relative to the linear model lines and train the appropriate pathway for improvement. Focusing on the strengths and weaknesses of an individual rider, at a given time.

The linear model and its lines of best fit define a parabolic power duration curve. These lines of best fit and power duration curve are used throughout this thesis, with no refitting or reidentification, in analyzing sex differences and different race durations, to show their generality and robustness, including the addition of independent additional datasets in some analyses. The linear model is also compared to a range of existing power metrics to delineate the advantages and disadvantages from a physiological and coaching perspective of this simple model and its implications. While the other equations are close in their relationships to the linear, the linear is the simplest model to use and more practical for application to the coaching of track sprint cyclists.

Chapter 4: Comparison of the power-duration relationship comparison in competition sprint cyclists from 1-s to 20-min

Data presented within this chapter has been published in:

H. A. Ferguson, C. Harnish, S. Klich, K. Michalik, A. K. Dunst, T. Zhou, and J.G. Chase, **Power-duration relationship comparison in competition sprint cyclists from 1-s to 20-min. Sprint performance is more than just peak power.** PLOS ONE 2023 Vol. 18 Issue 5 Pages e0280658

4.1 Introduction

Current coaching convention places peak power as the main determinant of sprint cycling performance. The study in this chapter challenges the notion and compares two common durations of sprint cycling performance with not only peak power, but power out to 20-min. Equally, there is also a related belief in sprint cycling coaching, where maximal efforts of longer durations will be detrimental to sprint cycling performance. Again, this belief has not been significantly analyzed or challenged with data. This study follows on from Chapter 3 using the analysis presented to try and show the importance and potential of training durations from 1-s to 20-min over a preparation period to improve competition sprint performance.

Sprint track cycling at Olympic Games and Elite World Championship levels is a subsection of cycle sport requiring a combination of peak speed, power, strength and short term endurance (speed endurance) [34]. While sprint cycling requires both a high level of strength and power, the nature of racing is actually more within the speed-endurance realm [315]. Unlike Olympic Weightlifting, powerlifting, or peak power field events, all sprint cycling races (team sprint, 500/1000-m time trial, match sprint and Keirin) range in durations from 15-s to 75-s depending on the event [34, 184]. Events longer as 75 s duration are performed by endurance cyclists specialized in pursuit races (team and individual), omnium and the Madison taking 135-300 seconds [35, 64, 65]. More recent study focuses on gear selection to rapidly achieve a maximum cadence to manage fatigue and sustain sprint performance over race durations [60, 61, 316].

The principle of specificity is a key component of preparation for sprinting performance [45, 47, 317]. Current models of sprint cycling performance appear inadequate to develop optimal performance in competition sprint cycling [34]. The reliance on peak power as a singular, simple, and primary predictor of sprint cycling performance appears to be more about convenience than empirical evidence [128, 318-320]. Ergometer-based testing performed in the laboratory is widely used to assess this value, but without comparison across different durations. In addition, it cannot cover the fact successful performance in track-sprint cycling is multi-factorial, incorporating physiological traits, tactics, and other specific skills [58, 125, 226, 321, 322].

Despite data showing the reliance on both oxygen independent glycolytic and oxidative energetic pathways for durations associated with competition sprint cycling [171-174, 323], the priority of training is focused on peak power [156], peak strength in the gym [318, 320], and maximal torque after the cycling-specific isometric resistance training [161]. The application of this approach has limited empirical evidence [184, 324]. Stone et al. [324], show a relationship between various strength exercise measures and standing start performance (25-m – 333.33-m). However, this research lacks a comparison with longer durations to determine if the relationship remains as distance increases, so the model is incomplete, and the conclusions may be self-fulfilling without comparison across a wider domain of durations.

Dorel et al. [184], concluded, peak power relative to frontal area or pedaling frequency, was a strong predictor of flying 200-m performance on a velodrome. However, the study did not investigate the role of average power, average cadence, or average frontal area/power on flying 200-m performance. Thus, again, the lack of comparison means the conclusions drawn may not be complete or give a full picture of the relationship between power and performance.

The anaerobic speed reserve, developed to model track running performance for events from 10-s – 300-s, is based on maximal sprinting speed and maximal aerobic speed (the lowest running velocity at which $\dot{V}O_{2max}$ may occur) [325]. Using a power meter, this concept has been applied to cycling, called the anaerobic power reserve (APR) [267]. Similarly, the critical power (CP) model has been used to model performance over short, medium and long durations reflecting exercise domains (heavy, severe, extreme) [326-328]. An advantage of this model is it allows the determination of a critical power for durations between 2-15-mins [329], and also an estimate of finite high intensity energy referred to as *W'* and measured in kilojoules[326].

The APR and CP models may provide a useful means of predicting the power-duration relationship in the extreme exercise intensity domain, such as during sprint track cycling events Leo et al. [329]. It is questionable whether it is necessary to run multiple trials to predict performance given the ease of measuring actual performance [330], modelling the determinants from actual performance [316, 331], and measuring performance with various sensors, especially power output, during competition [216].

Thus, the literature is replete with studies on peak power in relation to sprinting. It also contains some coverage of performance over competition durations of 15-75s. However, there is much more sparse reporting on multiple sprint performance (qualifying rounds, intermediate rounds, and medal finals), which form the basis of all world championship sprint events Finally, there is no research on the effect of longer duration efforts within a training period on the performance of sprint cyclists, because, as noted, they are deemed detrimental and thus their relationship to power at sprint event durations has not been examined to date.

The study in this chapter compares mean maximal power in sprint cycling across a wider range of durations from 1-s to 20-min to assess the validity of assumptions in current training approaches [318, 320]. It thus aims to show the inter-relationships of power across a range of training durations in sprint track cyclists. It uses the linear models found to be the best in Chapter 3 to assess these inter-relationships. More specifically, study in this chapter specifically hypothesizes:

A. There are strong consistent correlations between sprint cycling power at two common sprint competition durations of (15-s and 30-s) to power durations from 1-s to 20-min.

B. The slope of the regression lines will show all durations measured from 1-s to 20-min have a positive effect on sprint cycling performance.

If validated, these hypotheses would indicate a relationship between power across all track cycling event durations. Equally, positive correlations and slopes would indicate the trade-off in training a specific duration versus the event specific duration, where longer durations account for the endurance capacity required to sprint over multiple races in a given event.

4.2 Methods

4.2.1 Data Acquisition

Data were obtained from the publicly available open-access fitness depository www.strava.com [332], and downloaded according to Strava Privacy Policy (https://www.strava.com/legal/privacy) with no identification of people used in the study. Based on the public accessibility of the data the University of Canterbury Human Research Ethics Committee exempted this research from seeking ethics approval (2022/06/EX) without need of informed consent. Sprint cyclists were identified by matching Strava data with performances at New Zealand national track cycling championships [333], and World Masters Track Cycling Championships [334].

The data from Strava to determine weight, sex and age for the rider data. The Sauce extension (https://www.sauce.llc/) to download a *.tcx format file containing power meter data from Strava data of athletes competing at New Zealand sprint cycling competitions. Ride files uploaded to Strava from competition, and training sessions for 3-12 months prior to each NZ sprint championship event with available data.

4.2.2 Participants

A total of 27 participants, including 7 junior U17 – age 15/16 yo in year of competition; 4 U19 – age 17/18 yo in year of competition; 8 elite – age 19-34 yo in year of competition; and 8 masters – 35+ yo with assignment in 5-year age groups (8 participants), sprint track cyclists (Table 4.1). The classification of sprint track cyclists was made from the ability to place top 4 in the sprint in U17, U19, and Elite levels, top 4 in Keirin for U19, Elite and Masters, top 4 in time trial (500-m for women, 1000-m for men) in all grades, competing at Junior World level in sprint events, and top 4 placing in Masters World Championship events. Data from power meter measures were collected during testing, training, and racing sessions over a cross-section of male (21) and female (6) track cyclists. Datasets (N=144) from endurance track cyclists (N=69) used in the authors' prior research were used as a comparison group; power meter measures were collected during testing, training, and racing sessions over a cross-section of 60 male and 9 female track cyclists [315].

Table 4.1: Participant data included in this study, where endurance (END) cyclists are a separate cohort from sprint cyclists as shown and highlighted. Median and interquartile range [IQR]. Sprint cyclists are the first set of unlabeled data sets.

	All	Male	Female
Data Sets	56	44	12
Participants	27	21	6
Age (years)	19 [16 - 39]	25 [16 - 40]	17 [16 - 19]
Weight (kg)	76.5 [74.0 - 86.8]	80.3 [75.0 - 88.0]	64.0 [60.0 - 74.0]
END Data Sets	144	128	16
END Participants	69	60	9
END (Age)	26 [17 – 38]	27 [17 – 39]	19 [17 – 30]
END (Weight)	70.0 [65.0 – 75.5]	72.0 [67.0 – 76.0]	57.0 [56.0 – 63.5]

4.2.3: Study Overview

The data in this study is first distinguished by comparing to a group of endurance (END) track cyclists to assure the study was only considering and testing data from sprint cyclists [315]. The 15-s duration reflects the flying 200-m where the riders jump 100-m - 125-m from the 200-m mark on the track, the first lap of Team Sprint and the shortest duration match sprints take place over. Similarly, 30-s duration reflects a 500-m time trial, riding *2nd wheel* (2nd rider in the starting line-up) in the team sprint, a long match sprint, and/or the Keirin event. These two common durations of sprint cycling where compared against several durations from 1-s to 20-min to test the two hypotheses.

4.2.4: Power Meter Data

This study uses power meter data, which measures power in watts at 1-s intervals, as variables. Only cyclists who use a power meter model allowing regular calibration [113] were selected, and only those who perform a zero offset before each use to account for temperature changes based on racing observation. A total of 28 of the cyclists used an SRM (SRM, Jülich, Germany) brand power meter and one used an Infocrank (InfoCrank Classic, Verve Cycling, Perth AUS) brand. This data was uploaded to the WKO5 (TrainingPeaks, Boulder, CO) sport data analysis software. The max mean power was obtained for each participant for 1-s, 6-s, 12-s, 15-s, 18-s, 24-s, 30-s, 40-s, 50-s, 60-s, 90-s, 2-min ,3-min ,6-min ,12-min and 20-min durations in WKO5.

The data was analyzed to determine the relationships between all durations and two common sprint cycling performance durations (15-s and 30-s). The slope for the two sprint durations and all other durations are compared to a 1:1 relationship (15-s:15-s and 30-s:30-s power). The data included maximal efforts over all durations from racing, testing, and training sessions. Endurance cyclist data from previous research [315] was used (Table 4.1) to validate the data and compare with to sprint cyclist data, where this comparison is specifically used to show the sprint cyclist data is composed only of sprinters based on their expected differences in power at sprint and endurance durations.

4.2.5: Analyses

Matlab version R2021a (The MathWorks, Natick, MA) was used to perform the descriptive statistics including mean maximal power and interquartile range and the statistical analysis. Model quality is assessed by total least squares correlation coefficient, R^2, to account for variability and error in both variables [311, 312]. A higher R^2 value indicates a stronger relationship and a better model and predictor. Model slope indicates the trade-off between power interval training and peak 1-s power. Jamovi version 2.2.5 (The Jamovi Project, Sydney, Australia) statistical software was used to conduct a Welch's t-test for unequal sample sizes and variances to compare the differences in power between the sprint and endurance groups to ensure the study group were sprint cyclists in terms of power metrics [335]. P-values of <0.05 for the *t*-test were considered statistically significant.

4.3 Results

4.3.1 Assuring a Sprint Cohort

Table 4.2 shows the results of the Welch's *t*-test between sprint and endurance cyclists from prior research [315]. It describes the difference between sprint and endurance groups in Table 4.1 for all durations except 30-s W/kg. The sprint group delivers higher power than the endurance group for durations below 30-s and lower power for durations above 30-s (3-min and 20-min), as would be expected across these groups and durations. These data indicate the national level sprint cyclist data collected were different from a group of national level endurance cyclists in an expected way for sprint cyclists. Fig. 4.1 illustrates the differences between the male and female sprint and endurance groups.

Table 4.2: Independent Samples T-Test between sprint power output (PO) in watts per kilogram and endurance PO for selected durations, where sprint durations are 1-30-s and endurance power durations are 3-min and 20-min.

PO W/kg	Statistic	df	p-value
1-s	2.362	73.1	0.021
15-s	2.163	70	0.034
30-s	0.612	74.4	0.542
3-min	-6.591	64.4	< .001
20-min	-10.447	68.5	< .001

4.3.2 Sprint Cycling Power Across Durations

Table 4.3 shows the R2 values and slopes for 15-s and 30-s against power at all durations. The main result was the high coefficient of determination for 15-s and 30-s ($R^2 \geq 0.86$; $R^2 \geq 0.83$, respectively). Correlations were strong for durations longer than the 15-30-s durations most associated with sprint cycling performance.

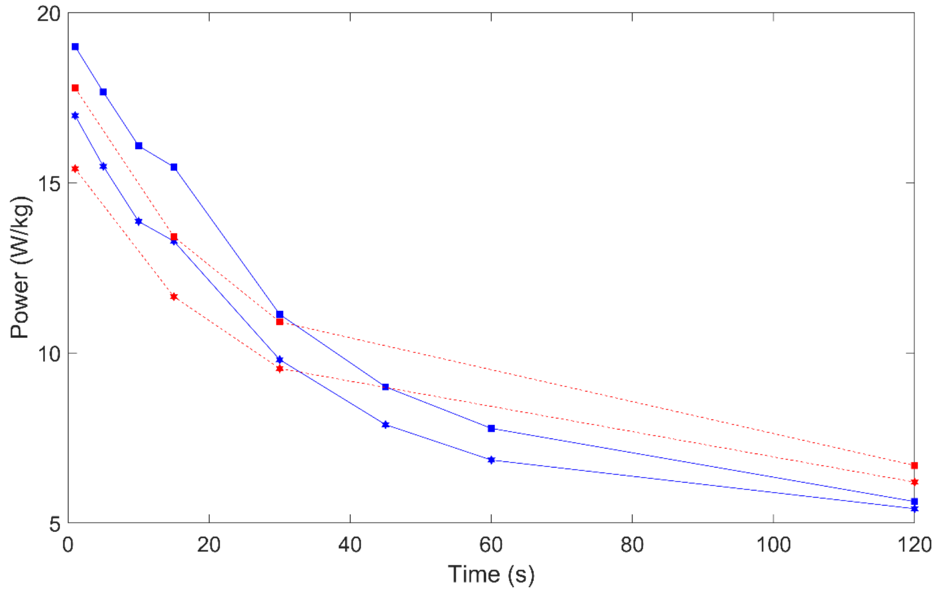

Fig. 4.1: The comparison of power (W/kg) for female (hexagon) and male (square) sprint (blue line) and endurance (red dotted line) track cyclists from 1-s to 2-min measuring peak power.

Similarly, Fig. 4.2 shows the matrix of correlation coefficients comparing all power durations. Each power duration was perfectly correlated to itself, as expected. The minimum values are all $R^2 \geq 0.83$, showing there are no distinguishable or large differences in correlations between power across all durations [336], and all the correlations are strong. Table 4.3 and Fig. 4.2 respectively support the first hypothesis.

The slopes in Table 4.3, and Fig. 4.3a and 4.3b show an increase in power at all durations has a strong relationship on two common durations of sprint cycling performance. An increase in any max mean power from 1-s to 20-min had a strong relationship on two common durations of sprint cycling performance. Fig. 4.3 and Table 4.3 respectively confirm the second hypothesis.

Table 4.3: R^2 and slopes for 15 and 30 second power and power at all durations

Time	R^2 15-s	Slope 15-s	R^2 30-s	Slope 30-s
1-s	0.94	0.78	0.89	0.59
6-s	0.97	0.83	0.90	0.65
12-s	0.99	0.92	0.91	0.73
15-s	1.00	1.00	0.93	0.78
18-s	0.99	1.07	0.94	0.82
24-s	0.96	1.16	0.98	0.93
30-s	0.93	1.26	1.00	1.00
40-s	0.90	1.50	0.97	1.16
50-s	0.89	1.65	0.94	1.30
60-s	0.89	1.84	0.93	1.41
75-s	0.88	2.09	0.91	1.58
90-s	0.88	2.23	0.90	1.72
2-min	0.88	2.47	0.89	1.92
3-min	0.87	2.67	0.87	2.09
6-min	0.87	3.25	0.85	2.47
12-min	0.86	3.59	0.84	2.76
20-min	0.86	3.88	0.83	2.96

W/kg	1s	6s	12s	15s	18s	24s	30s	40s	50s	60s	75s	90s	2min	3min	6min	12min	20min
1s	**1.00**																
6s	0.98	**1.00**															
12s	0.95	0.98	**1.00**														
15s	0.95	0.97	0.99	**1.00**													
18s	0.93	0.96	0.98	0.99	**1.00**												
24s	0.92	0.93	0.95	0.96	0.98	**1.00**											
30s	0.90	0.90	0.92	0.94	0.95	0.98	**1.00**										
40s	0.87	0.87	0.89	0.91	0.92	0.95	0.97	**1.00**									
50s	0.88	0.88	0.89	0.90	0.90	0.93	0.95	0.98	**1.00**								
60s	0.89	0.88	0.89	0.90	0.90	0.92	0.94	0.97	0.98	**1.00**							
75s	0.89	0.89	0.89	0.89	0.89	0.90	0.92	0.95	0.97	0.99	**1.00**						
90s	0.89	0.88	0.88	0.88	0.88	0.88	0.90	0.93	0.95	0.97	0.99	**1.00**					
2min	0.90	0.89	0.89	0.88	0.88	0.88	0.89	0.92	0.94	0.95	0.96	0.98	**1.00**				
3min	0.90	0.89	0.89	0.87	0.86	0.87	0.88	0.89	0.90	0.92	0.92	0.93	0.96	**1.00**			
6min	0.91	0.89	0.88	0.87	0.86	0.85	0.86	0.87	0.87	0.89	0.89	0.90	0.93	0.96	**1.00**		
12min	0.91	0.89	0.88	0.87	0.86	0.84	0.85	0.85	0.85	0.85	0.86	0.88	0.88	0.92	0.96	**1.00**	
20min	0.91	0.89	0.88	0.87	0.86	0.84	0.83	0.82	0.83	0.84	0.84	0.85	0.86	0.88	0.94	0.99	**1.00**

Fig. 4.2: R^2 comparing correlation across all durations. The values for sprint cycling durations of 15-s and 30-s are highlighted showing consistent strong correlation across all power ranges.

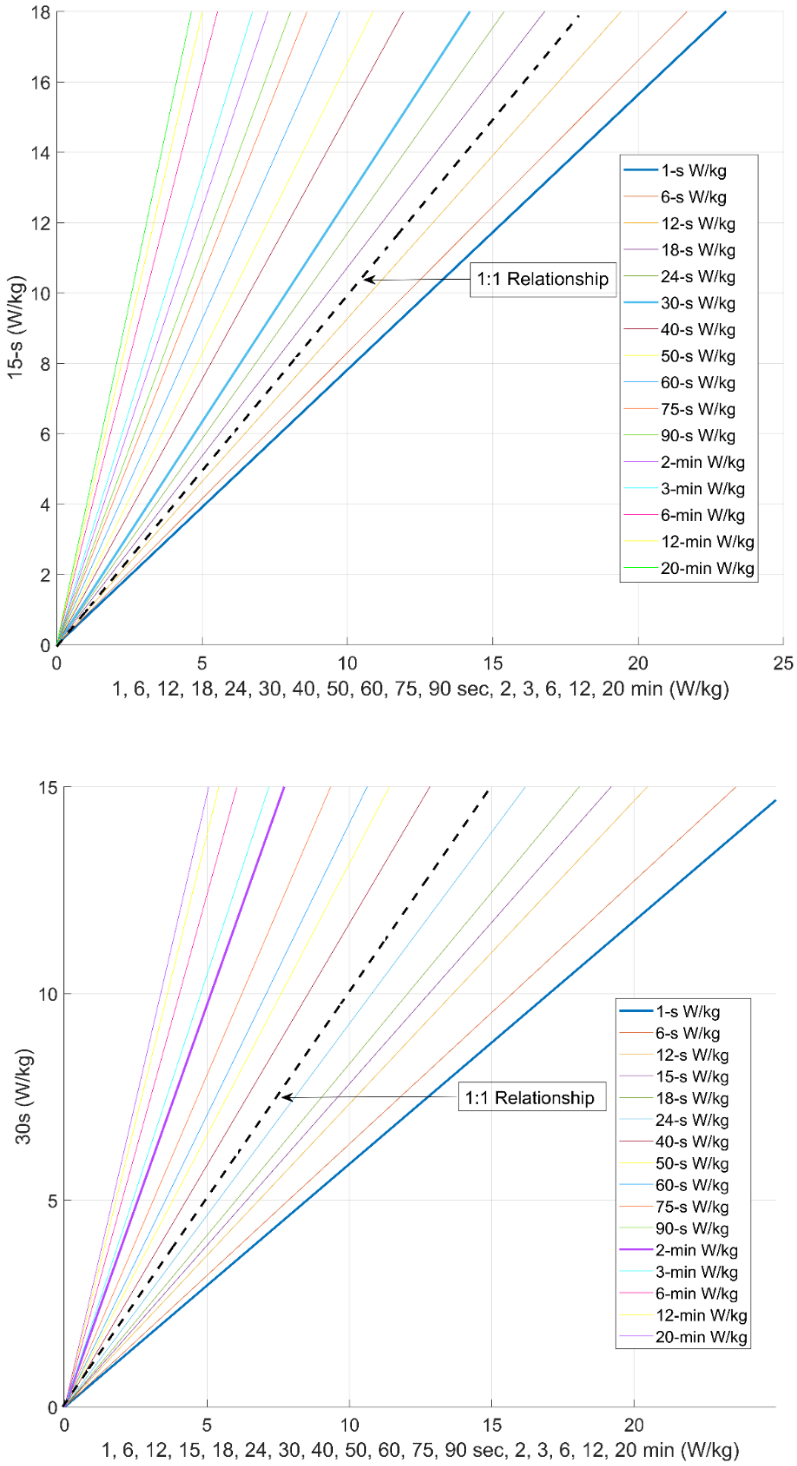

Fig. 4.3: TOP: lines for watts/kg 15-s against W/kg for all durations studied; and BOTTOM: slopes for W/kg 30-s against W/kg for all durations studied.

4.4 Discussion

The purpose of this study was to compare 15-s and 30-s power in sprint cyclists, with a range of durations from 1-s to 20-min. This chapter hypothesized strong correlations across all ranges of power measured from 1-s to 20-min, contrary to current coaching belief and practice. These data are the first to demonstrate strong relationships between two common durations of sprint cycling competition performance with power durations from 1-s to 20-min. Therefore, the results can be used to propose beneficial training durations within this range. More specifically, maximal efforts of up to 20-min may be warranted to complement sprint cycling training and will not detract from sprint cycling performance within a training period of 3-12 months based on these data.

Slopes for all power durations indicate the strongest relationships are for 15-s and 30-s power (Fig. 4.2). The 1-s power slope has the same slope as 2-min power, which indicates all the durations between these values are important to train to influence sprint performance. This outcome is also contrary to current coaching practice and belief in the field, and these results provide considerable evidence supporting a different approach. Based on use of data from a 3–12-month training period, what is not specific to this research is when these relationships should be developed. The 20min relationship to sprint cycling power should be trained early in the process, moving towards shorter duration training times, and leading into keys events, focusing on sprint power performance, a periodized approach. The line of best fit for a group, offers a way to test each individual, and by training towards the line where a rider above the line (high in race winning power) would train for capacity, and a rider below the line of best fit (high in speed endurance), would train more for race winning power.

In particular, 1-s power predicts performance for both 15-s and 30-s power, but 6-s, 12-s, 18-s, and 24-s power predict 15-s power better. Likewise, 6-s to 90-s power (except for 20-s and 30-s) predict 30-s power better than 1-s power. This result suggests longer time intervals should be used in power-duration modelling, not only the peak power in the ~10-15 s sprint effort, as Sanders and Heijboer [267] also proposed.

This analysis can help profile cyclists who need to race maximally for 15-30 s, such as in sprint and Keirin events. The exact duration of each race depends on the group dynamics [34, 125, 226]. Cyclists who have high power output but are above the line of best fit may need to increase their power endurance and repeatability. These are important for medal-winning in championship sprint events which require multiple efforts.

A limitation of this data is the group consists of national level sprint cyclists in Junior (under 17), under 19, elite and masters categories, and riders in age group world events: Junior Worlds (16-18) and masters (35+ in 5-year groups). The data differs from endurance cyclist data, but the participants may do more endurance riding and racing than a high-performance group. This difference may reflect tradition or analysis of sprint cycling performance demands.

This data is from national level sprint cyclists who trained and raced for 3-6 months. They likely did 20-min peaks early in a general preparation phase [337]. Shorter duration efforts are more likely to be performed in the lead up to competition. This assumption reflects the common periodisation of training focusing on three distinct periods of general preparation, specific preparation and peaking for key events [337]. Some training programs utilize a *short to long* approach, focusing on peak power, and adding speed endurance leading into competition [338]. However, the data presented here suggests a focus on 1-s is potentially to the detriment of actual performance when developing power around competition times has a closer relationship. Future research should develop power profiles for sprint cyclists to see if they need to build capacity or power for sprint cycling durations. Elite programs should try both capacity and 1-s power. With strong links between sprint power and 20-min power, longer efforts may help develop better sprint cyclists.

4.5 Summary

The study compared maximal efforts for peak-, short-, medium- and long-term power with power at 15-s and 30-s sprint cycling durations. The strongest links were with durations around 15-s and 30-s, confirming the first hypothesis. Performance at 2-min to 20-min durations correlated strongly and did not harm 15-s or 30-s power predictions, in fact they enhanced it, confirming the second hypothesis.

Coaches can use this data to plan training using endurance durations to improve sprinting performance. Depending on the strengths of athlete and the training period. In the early season the athlete can perform over aerobic durations with confidence this will not harm performance and improve their all-round capacity for sprint competitions. Closer to key events it is clear a rider should focus more on their 15 – 30 second power. Also, a sprinter high in capacity could perform some shorter than competition duration efforts to ensure they and ready for competition training.

Chapter 5: Modelling sprint cycling sex differences using power data

Data presented within this chapter has been published in:

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5.1 Introduction

Currently, there are no data on sex differences in the power profiles in sprint track cycling. The cross-section study in this Chapter analyses retrospective data of female and male track sprint cyclists for sex differences, based on the results of Chapters 3-4. In particular, it hypothesizes women will exhibit lower peak power to weight than men, as well as demonstrate a different distribution of power durations related to sprint cycling performance.

Track cycling is a sub-section of cycle sport, including the sprint events: individual sprint, Keirin, time trial (female 500-m and male 1000-m), and the team sprint [321]. With the exception of the time trial, the races are similar for both sexes, and men and women compete in the same events at the Olympic Games [34]. Thus, it is common practice in sprint performance training, for male and female riders to train the same [47, 219].

Although the demands of competition are similar, there are sex differences in the anatomy and physiology of elite-level track sprinters [339-343]. Sex differences were observed in muscle fiber distribution, fiber size, and levels of succinate dehydrogenase, lactic dehydrogenase, and phosphorylase of sprint runners [159]. Similarly, sex differences were observed in running 100-m and 200-m sprinters measuring accumulated oxygen deficiency, but not lactate or phosphocreatine measures [179]. Female athletes showed less fatigue than males in knee extensor contraction, which was independent of strength [344]. Females had a higher critical intensity relative to maximal force than males, and this difference was observed above and below a metabolic threshold [345]. While there were no differences in fatigue along the power-duration curve, relative to a maximal ramp test, the mechanisms of fatigue differed between sex [346]. Aerobic contribution to a 30-s Wingate Anaerobic Test (WAnT) was 20% for men, but increased to 25% for women [347]. All these differences suggest training sprint cyclists should be sex-specific, corresponding to their physiological differences, and in contrast to how they are trained (the same) currently.

The author of this thesis found no studies on the sex-specific training of sprint cyclists. Previous research reported differences in peak power output (PPO) between men and women from the laboratory based WAnT tests in intercollegiate athletes [348], and also elite speed skaters [349]. It should be noteworthy, because PPO is still an important factor in predicting sprint track cycling performance [184], and peak power output related to body mass expresses the ability to accelerate effectively, which is a key factor in sprint cycling events [154].

Dunst et al. [60] collected data to calculate force-velocity profiles from field tests consisting of maximal 65-m sprints on a cycling track with different gear ratios. Interestingly, no one compared sex differences of PPO derived from specific track cycling training sessions. In addition, there are also no studies modelling the performance of female sprint cyclists in competition. Estimates of performance can be drawn from descriptive laboratory tests and from prospective studies investigating various training protocols or nutritional supplements, which use a performance test similar to the competition demands of sprint cycling [184]. However again, there is a paucity of research using data from national or elite female sprint cyclists.

Nimmerichter et al. [110] compared PPO measured in the laboratory and track field-based trials (10-s, the 60-s, and 180-s) in adolescent cyclists. Higher results obtained in laboratory tests were explained by experience to optimize gearing and cadence, but also might be attributed to the technical ability of the young cyclist. With the challenges of obtaining physiological measures in the laboratory, let alone in the field, the use of various models based on performance data from either velocity or power data have been proposed to explain sprinting performance [315, 316, 331]. However, these models do not always adequately capture performance outcomes [350]. Hence, there remains a need to consider data and models accounting for sex specific response's to training and quantifying these differences to better guide training approaches.

Overall, there is a dearth of research on the training of sprint cyclists of either sex, as well as no apparent research modelling performance of female sprint cyclists in competition or training. The paucity of research using data from female subjects, let alone female sprint cyclists, is sorely lacking. As a result, there is no insight on how female cyclists differ from males, and thus no evidence upon which to adjust training.

Therefore, the study in this chapter retrospectively analyzed open-source, publicly available power meter data of elite male and female track cyclists do identify sex differences power, performance, and potentially energy system involvement (ATP-phosphocreatine, glycolytic and oxidative [154]). Based on observed physiological differences, the study hypothesizes:

A. Women will display differences to men in, in their sprint duration power, which could have meaningful implications on training for female sprint cyclists.

5.2 Methods

5.2.1 Participants

The open source www.Strava.com website was used to identify sprint cyclists competing in New Zealand who posted both their racing, testing and training data [332]. Using Strava, data was obtained from 29 track sprint cyclists (8 women and 21 men). The use of a single, open-source site ensures all data was stored similarly, and any computations used similar data structures and density. The University of Canterbury, Christchurch, New Zealand Human Research Ethics Committee gave an exemption for ethics approval due to the publicly available nature of the data (2022/06/EX).

Table 5.1 describes the participants for this study, and also the endurance data from Ferguson et al. [315]. Retrospective power meter data during training and racing from a group of 6 women provided 18 datasets, and 21 men provided 56 datasets. The inclusion criteria for classification as a sprint cyclist was the ability to place top 4 in the match sprint, Keirin, and track time trial events, competed at the Junior World level in sprint competition, and top 4 placing in Masters World Championship events [333, 334].

The final inclusion criterion required data for a range of durations spanning energy systems from ATP-phosphagen (1-6 s), oxygen-independent glycolysis (6-40 s), and oxidative (over 40-s) energetic pathways [170]. Specifically: 1-s, 5-s, 10-s, 15-s, 30-s, 45-s, 60-s, and 2-min, over a minimum of 3 months, and a maximum of 12 months. Data included maximal efforts over all durations from racing, testing, and training sessions. Two datasets were excluded from the study, because the athletes, endurance power indicated they had not performed a maximal effort.

To validate this data, the study uses endurance cyclist data from previous research [315], to compare with the sprint cyclist data. Recorded power [W/kg] measurements were used to establish the study uses data from sprint cyclists compared to endurance cyclists for the durations of 1-s, 15-s, 30-s, 60-s, and 2-min.

Table 5.1: Participant data included this study with sprint data sets in the first set and the validation endurance cyclist data sets and demographics in the second. The median and interquartile range (IQR) are presented.

	All: Median [IQR]	Female: Median [IQR]	Male: Median [IQR]
Sprint Data Sets			
Data Sets	72	18	54
Participants	29	8	21
Age (years)	30 [17 – 41]	23 [17 – 27]	33 [17 – 43]
Weight (kg)	77.9 [75.0 – 84.5]	65.9 [60.0 – 73.8]	82.0 [75.0 – 88.0]
Endurance Data Sets [315]			
Data Sets	144	16	128
Participants	69	9	60
Age (years)	26 [17 – 38]	19 [17 – 30]	27 [17 – 39]
Weight (kg)	70.0 [65.0 – 75.5]	57.0 [56.0 – 63.5]	72.0 [67.0 – 76.0]

5.2.2 Power Meter Data

All variables in this study used power meter data, measuring power in watts using 1-s intervals. An inclusion criterion for power meter data, was the use of a power meter model allowing regular calibration [113], and before each use, performing a zero offset was performed to account for temperature changes. The author collected the data via Strava and saved it in the WKO5 (TrainingPeaks, Boulder, CO) performance data analysis software. WKO5 was used to summarize peak power for all durations.

5.2.3 Study Overview

With data collected from periods including testing, training, and racing sessions, focused on sprint cycling competition performance. Thus, peak power was collected for 1-s, 5-s, 10-s, 15-

s, 30-s, 45-s, 60-s, and 2-min durations, where 15-s is the sprint race power duration. This data was analyzed to determine relationships between all durations and 15-s peak power, which reflects the power demands of the flying 200-m, match sprint, and the first rider in the team sprint [34]. While some sprints may take longer than 15-s, and up to 30-s – 45-s depending on events and tactics, the 15-s duration best reflects the nature of sprint cycling and is the comparator in this study.

5.2.4 Analysis

Peak power values for all durations are compared to those at 15-s to generate a power curve between 15-s and the input duration. Model quality is assessed using the total least squares correlation coefficient, R^2, which accounts for variability and error in both variables [311, 312]. Higher R^2 values indicate stronger relationships, and thus, a better model and predictor.

Linear model slope indicates the trade-off between power for a given duration and 15-s. Each slope is assessed against the 1:1 relationship found where 15-s and 15-s are compared, where the difference from 1:1 shows the trade-off between the two durations. The model includes the point (0,0), a point of null power. This assumption is physiologically relevant, where a rider could not have a measurable W/kg of zero at one duration and a zero value at another, as they should both be 0.0 at the same point.

The two-tailed independent t-test with Welch's correction was used to compare the differences in power between the sprint cyclist data and endurance groups, and thus to ensure the analysis group was truly comprised of sprint cyclists. A similar test was performed to measure differences between the male and female groups at each duration using 15-s as a dependent variable. The difference was significant as $p < 0.05$. Matlab version R2022a (The MathWorks, Natick, MA) was used to analyze the data. The hypothesis expects a difference between male and female cyclists in this latter set of comparisons, and specifically different slopes for these models, reflecting differences in physiology. Thus, differing slopes between male and female athletes supports the main hypothesis in this study.

5.3 Results

5.3.1 Assuring a Sprint Cohort

Table 5.2 displays the t-test for sprint versus endurance cyclists to show the sample of sprint cyclists have higher short-term sprint power and top-end aerobic power than track and road endurance cyclists. As expected, as the power duration extends to 2-min the endurance cyclists display higher maximum mean power, further validating this selection of sprint cyclists against endurance cyclists. $P \leq 0.05$ for all durations show the sprint group selected are different from the endurance rider group, and thus the study is assuring only sprint cyclists.

Table 5.2: Independent Samples T-Test for sprint and endurance cyclists of Table 5.1 for 1-s, 15-s, 30-s, 45-s, 60-s and 2-min.

W/kg	Statistic	df	p
1-s	-5.49	10.4	< .001
15-s	-4.19	10.2	0.002
30-s	-3.31	10.6	0.007
45-s	-2.52	11.2	0.028
60-s	-3.14	11.2	0.009
2-min	-3.21	12.2	0.007

Table 5.3 summarizes the power [W/kg] data for all subjects. It shows the power for each duration, and includes power for 1-s, 15-s, 30-s and 2-min durations for endurance cyclists [315]. Over shorter durations sprint cyclists have a higher W/kg than endurance cyclists, as expected between these two groups. For the 2-min duration, the endurance cyclists have a higher W/kg, again, as expected. For all durations, both sprint and endurance cyclists, female athletes have a lower W/kg than male athletes. As noted, all these outcomes match expectations.

Table 5.3: Descriptive data for both female and male, female, and male athletes for all durations, and in red the endurance (END) athletes [315] for 1-s, 15-s, 30-s, and 2-min. Median values and the interquartile range.

	BOTH (Median and IQR)	FEMALE (Median and IQR)	MALE (Median and IQR)
1-s W/kg	18.4 [19.69 – 16.82]	16.97 [17.57 – 16.01]	19.00 [20.43 – 17.83]
END 1-s W/kg	15.5 [19.08 – 15.67]	15.41 [15.63 – 14.55]	17.78 [19.25 – 16.31]
5-s W/kg	17.03 [18.69 – 15.51]	15.48 [16.26 – 14.15]	17.66 [19.29 – 16.35]
10-s W/kg	15.44 [17.20 – 13.68]	13.86 [14.56 – 12.57]	16.08 [17.34 – 14.60]
15-s W/kg	14.38 [16.32 – 13.29]	13.28 [14.19 – 12.21]	15.46 [16.71 – 14.15]
END 15-s W/kg	13.27 [14.59 – 11.88]	11.65 [12.26 – 10.29]	13.44 [14.71 – 12.11]
30-s W/kg	10.75 [11.55 – 9.69]	9.80 [10.70 – 9.12]	11.13 [11.76 – 10.00]
END 30-s W/kg	10.61 [9.86 – 12.03]	9.54 [10.28 – 9.09]	10.91 [12.05 – 9.93]
45-s W/kg	8.68 [9.45 – 7.73]	7.89 [8.17 – 8.17]	9.00 [9.58 – 8.22]
60-s W/kg	7.51 [8.04 – 6.68]	6.85 [7.31 – 5.94]	7.78 [8.08 – 7.14]
2-min W/kg	5.57 [6.10 – 4.74]	5.42 [5.88 – 4.74]	5.63 [6.39 – 4.82]
END 2-min W/kg	6.64 [7.20 – 6.15]	6.20 [6.58 – 5.91]	6.69 [7.30 – 6.21]

5.3.2 Comparing Female and Male Sprint Cyclists

Table 5.4 lists the R^2 value and slope comparing 15-s power [W/kg] against each of the durations. The R^2 values were different between female and male athletes, while the slopes between sexes were similar. Fig. 5.1 illustrates both slope and R^2 values for each of the durations in this study. This figure visually describes the data from Table 5.4 and illustrates the different spread of data for female sprinters compared to males, and the similarity of the slopes between sprinters of each sex.

Finally, Fig. 5.2 plots the differences for all durations between female and male sprint cyclists, and between female and male endurance athletes for selected durations. This illustrates the differences between female and male W/kg sprinters and illustrates how sprint cyclists have better short-term power at 1-s – 10-s, are comparable at 30-s, and at 2-min endurance cyclists have a higher W/kg.

Table 5.4: R^2 and slopes for 15 and 30 second power at all durations

Time	Female		Male	
	R^2 15-s	Slope 15-s	R^2 15-s	Slope 15-s
1-s	0.85	0.80	0.92	0.84
5-s	0.91	0.84	0.96	0.89
10-s	0.98	0.94	0.99	0.94
15-s	1.00	1.00	1.00	1.00
30-s	0.79	1.34	0.92	1.39
45-s	0.77	1.68	0.89	1.68
60-s	0.77	1.93	0.90	2.03
2-min	0.78	2.53	0.88	2.67

5.4 Discussion

This study retrospectively analyzed field-based power data from a group of elite male and female track cyclists to identify sex differences in power, performance, and estimation of energy system involvement. It hypothesized women would exhibit a unique short duration power duration curve, different from men. A difference in power as hypothesized would suggests implications for training female sprint cyclists differently from men.

The slope of the lines suggests the relationship between each duration and 15-s W/kg is similar for males and females with no notable differences. There is no difference in the relationship, between female and male riders for all durations used in this study. So, while male riders deliver a higher W/kg than female riders, and there are more intra-individual differences for females than for males, as seen in R^2 values, the slopes are similar. Thus, both female and male sprint cyclists should equally focus on both peak power, power specific to competition durations, and also to durations where oxidative energetic pathways predominate.

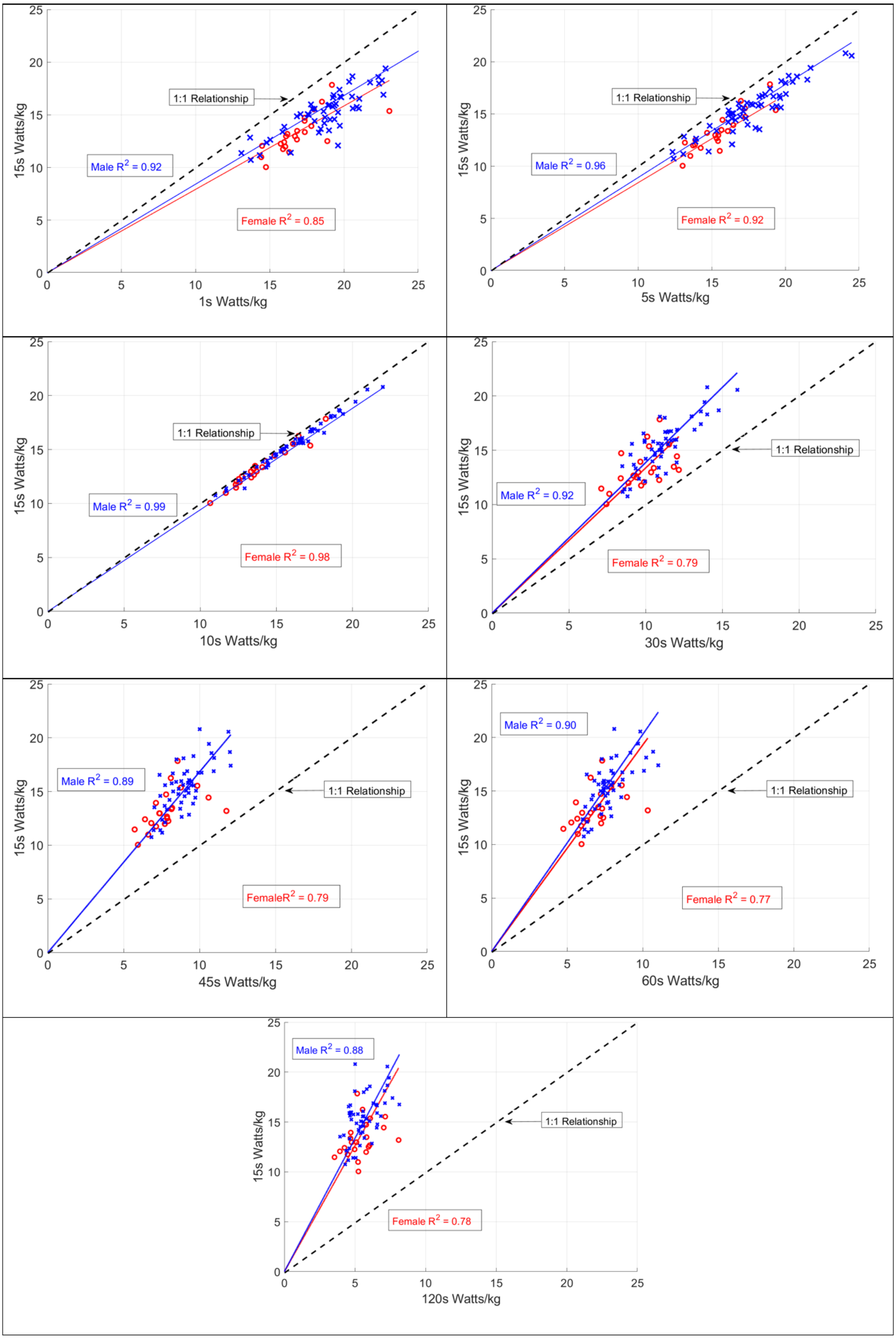


Fig. 5.1: Slope and R2 for 15-s W/kg and all durations in this study

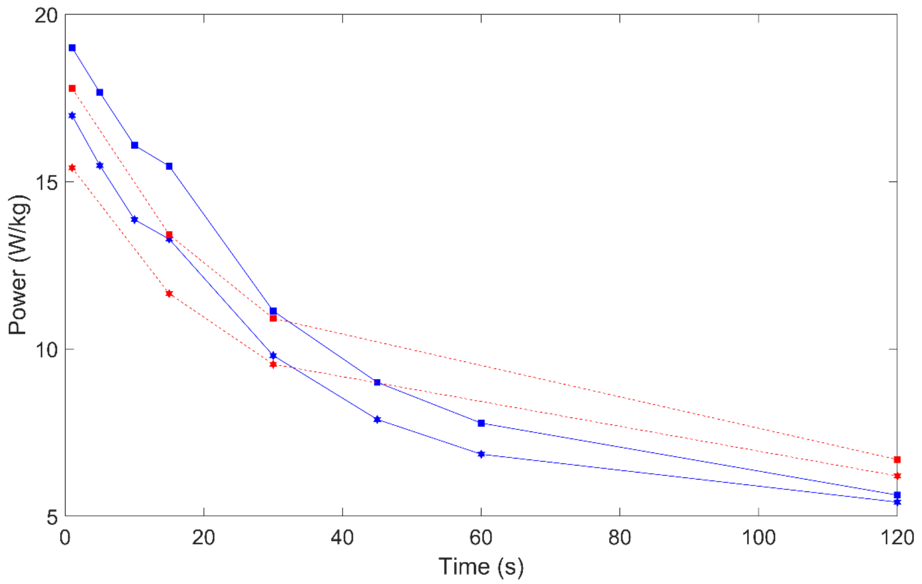


Fig. 5.2: The comparison of power [W/kg] for female (hexagon) and male (square) sprint (blue line) and endurance (red dotted line) track cyclists from 1-s to 2-min measuring peak power.

As a second main result, while the R^2 values for the data show a strong relationship for both male and female data (Table 4 and $R^2 \geq 0.77$ in all cases), the female data is more variable than the male data based on lower R^2 values for all durations except 30-s. This result highlights greater intra-individual variability among female athletes, despite similar power curves, and thus the potential corresponding need to individualize training for women as they vary more in how they relate to the line of best fit. Female athletes above the line will benefit from training their capacity to hold event-specific power for longer, while female athletes below the line of best fit would benefit from training to improve their event specific power.

A summary of the data for each duration for the sprinters, and selected data for the endurance riders, provides confirmation of the differences between sprint and endurance cyclists. The explanation for differences in W/kg is male cyclists weigh more, and performance cyclists (see Participants), will have a higher muscle mass, and thus be able to produce more power relative to bodyweight [351, 352]. A second common distinction is anatomical differences, which take shape as women mature from adolescence to adulthood [353, 354]. These differences were expected to result in different power curves, which was not the case in the main results.

Of note, the sprint cyclists were compared with a cohort of endurance cyclist data to clarify only sprint cyclists were being studied. The data showed for 1-s, 5-s, 10-s, 15-s, 30-s, and 60-s the W/kg for the sprint cycling group was higher than the endurance group, consistent with previous research [156]. For 2-min, the endurance group had a higher W/kg. This set of results is expected due to the higher aerobic contribution to performance in endurance athletes [173, 355]. Thus, overall, this analysis ensured the main analysis comprised only sprint cyclists.

The main limitation of this research is these athletes will not only focus on sprint training and sprint cycle racing. It is expected riders in this study would perform track endurance events and even short and flat road races. Elite sprint cyclists in a nationally funded program would be expected to be focused more on sprint-specific training and racing.

In a case study of New Zealand elite cyclists preparing for the 2012 Olympic Games, their training was purely focused on sprint performance [219]. However, testing metrics used in the preparation suggested performance was progressing towards the Olympics, but was not reflected in actual performance in competition [34]. Thus, there is a strong disconnect between the testing metrics used and performance outcomes, suggesting new models and approaches are required, potentially such as those suggested in the results in this chapter.

The data used was harvested from an open online source [332]. Athletes can elect to upload their data to Strava privately and can remove the power data component from viewing. It is also notable no data was found, public or private for High Performance Cyclists (NZ and

International). Public posting of this data could actually assist in efforts to monitor high performance cycling to control the use of illegal drug taking in sport [37, 42].

Limitations also arise, particularly for PPO or 1-s power, due to the use of power as a measure. Power for 1-s can be affected by the gearing selected [59], variations from standing start [356], and initiating a sprint in the seat, or out of the seat [357]. Due to the nature of riding on a velodrome with banked corners [166], and the power required to accelerate [358]. With the nature of sprint cycling in sprint competition where acceleration from a standing start, slow roll and from a fast pace the power to achieve sprint speed, power over the duration of the ride declines while speed is maintained [359].

Future research in this area should focus on the potential differences among female sprint cyclists. The higher variation within the women highlights the importance of prescribing individual training for female sprinters. Elite athletes are focused on maintaining the performance required to hold their position in professional or national training programs, rather than furthering the science of sports performance. However, professionalism should be balanced against the need to attain higher levels of performance to enhance the promotion of sport, trickle down into national, state and club sports, and to form links with general health and wellness.

The main application of this chapter is to ensure when developing the performance of female sprinters is to address the within-female individual differences, as these are wider than those seen in men. Collect data on the group of female sprinters to get a good line of best fit. Sprinters above the line should focus on the development of capacity, and those below the line should focus on developing the rate of energy provision over sprint durations. This strategy will ensure the athlete has both the power needed to perform at their best in competition, balanced with the capacity.

5.5 Summary

The data in this study shows the participants are sprint cyclists by comparison to a group of track endurance and road cyclists, however expected differences in power to weight between female and male athletes was not evident. The slopes comparing several power durations and sprint cycling power (15-s) are similar, suggesting female and male sprint cyclists have a similar relationship with power at durations from 1-s to 2-min and sprint durations, counter to the hypothesis. This outcome points towards women being more efficient in their use of energy pathways or using a different balance of energy pathways to generate power.

Second, the lower observed R^2 values for females compared to males shows much greater intra-individual variation in these relationships for females compared to males. This second result highlights the need for greater individualization of training for female athletes, as well as the need to measure female athletes, in particular, to make appropriate training decisions and ensure the athlete has a correct balance of power to ride fast and the capacity to sustain power over a competition duration.

Chapter 6: Training progression over a three-month period for track cycling sprinters

Data presented within this chapter has been published in preprint, and is under review for publication:

Ferguson, H.; Harnish, C.; Chase, J.G. **Performance Progression over a Three Months of Periodized Training for Track Cycling Sprinters.** *Preprints* 2023, 2023071992.

6.1 Introduction

There is a paucity of data on the progression of track cycling sprinters, and the evolution of training and performance over a training cycle. Following prior research showing relationships between sprint cycling power and endurance cycling power in Chapters 3-5, this chapter presents a study comparing these relations over a 3-month period. The hypothesis is large improvements in power would come from training either for sprint power or sprint capacity, and this outcome would be reflected in the data.

This chapter examines the potential of training relative to a position on a plot of endurance versus sprint power similar to the power curves in prior chapters. A specific goal is to examine how training "towards the line", whether in a position above or below the previously developed power relationship lines for two power durations, would provide the best gains in a period of training before a major event. The chapter takes a narrative approach to a series of riders in examining these outcomes, as this approach allows inclusion of confounding effects, such as injury, illness, or training which does not follow the goal. It thus examines riders and training towards peak events in the context of these power-duration curves, but without intervening, so the analysis is observational and narrative in assessing the hypothesis.

This study investigates the mix of training leading into a key competition, or performance challenge in track cycling sprint cyclists. Track cycling sprint cyclists are athletes who focus on shorter distance, high intensity and speed events [34]. Track cycling sprint cyclists need a mix of both pure speed to race between 65-80 kph for distances of 200-m to 1000-m, and the durability to race over several rounds, as all Olympic and World Championships sprint events require multiple performances to progress to the medal rounds. Getting the training mix correct is essential to ensure the rider reaches key competitions in the best physical form to meet event demands. The prioritization of training over different blocks of training should aim to develop both the speed and capacity to perform in racing, and the proportion of each should reflect the current fitness level of the athlete relative to the event demands [34].

There is limited research tracking sprint performance in a variety of events. One study looking at the progression of a national squad leading into the London Olympics showed a disparity, where improving testing measures in training were not subsequently reflected in results at the event [219]. Another study observed six high performance male athletes, towards a peak event, describing the training zones used [57]. While this study described the different training zones, and the split on-bike training to resistance training, it did not compare the training to resultant performance in a key event [57]. A study of 2 running sprint athletes who both opted for a periodized approach observed distinct changes in performance between preparation and competition phases [360].

However, most academic discourse is focused on discussing different coaching approaches [225, 318-320]. Further, most studies of sprint periodisation across many sports are based on short term studies using a student population, rather than an athlete population, whether performance or high-performance athletes. Finally, most studies have limited numbers of athletes, thus reducing the ability to draw any significant conclusions, either statistically or via the evidence as presented. All these issues reduce the ability to assess and quantify the impact of training on resulting performance outcomes.

Currently, the study of sprint cycling revolves primarily around the generation of peak power and how this single value translates into peak speed [34]. While this approach is a fruitful area of research to understand, peak power shares less of a relationship with performance over sprint durations than actual performance metrics [361]. Hence, there is a gap in linking peak power and sprint performance, which might be closed by assessing the impact of training across a range of sprint performance durations.

A better approach is to examine actual sprint performance and pacing of sprinting over an individual race and across races within a series or event. From these data, performance modelling could identify the strongest relationships between training approaches and competition performance. Recently, in Chapter 3 a model was presented (Fig. 6.1) where the slope of the line of best fit for a group of sprint cyclists indicates the qualities riders should develop [361]. For athletes below the line in Fig. 6.1, there is a need to train peak power, or towards the line, and for those above, the need to train for capacity, again towards the line. Fig. 6.2 illustrates the data used from Ferguson et al. [315] to determine the line of best fit. Code is provided in Ferguson et al. [361], which a coach or sport scientist can use to determine the line of best fit for a training group.

The discussion of sprint cycling periodisation revolves around two approaches, called *short to long*, and *long to short* [225]. Short to long, starts with peak power, strength and speed and adds speed endurance as the athlete approaches key events. Long to short, starts with capacity and progresses through to speed work. The challenge with these approaches is high performance athletes with Olympic aspirations are rarely used in academic research. There may be descriptive research based on current practice, but there is no testing of hypotheses where inferior performance may mean losing scholarships or sponsorships. Further the numbers of athletes in limited available studies are often quite small, limiting the potential conclusions drawn and the ability to generalize them to other riders.

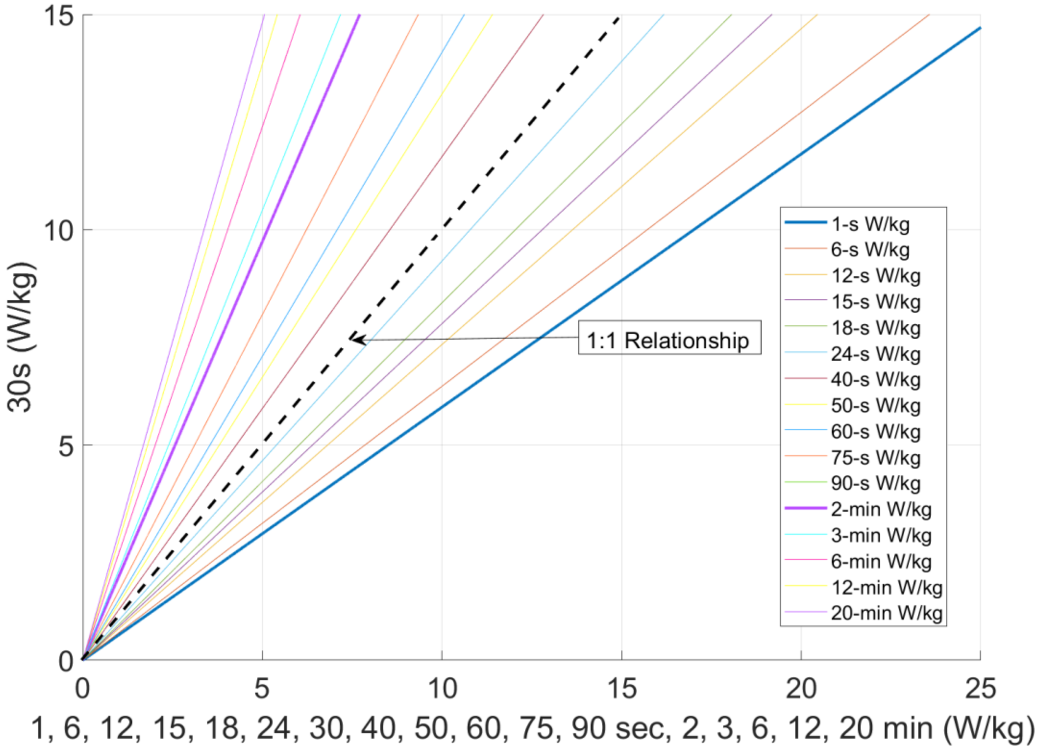


Fig. 6.1: Illustrating the line of best fit for various durations against a common duration of sprint cycling performance: 30-s.

This lack of analysis is where descriptive studies applying modelling to tease out the areas of performance with the strongest relationships can be useful. The approach requires a method of quantifying or understanding the relationship between speed and capacity. Such a tool would allow coaches or/and researchers to plot the progress of an athlete towards performance in a goal event.

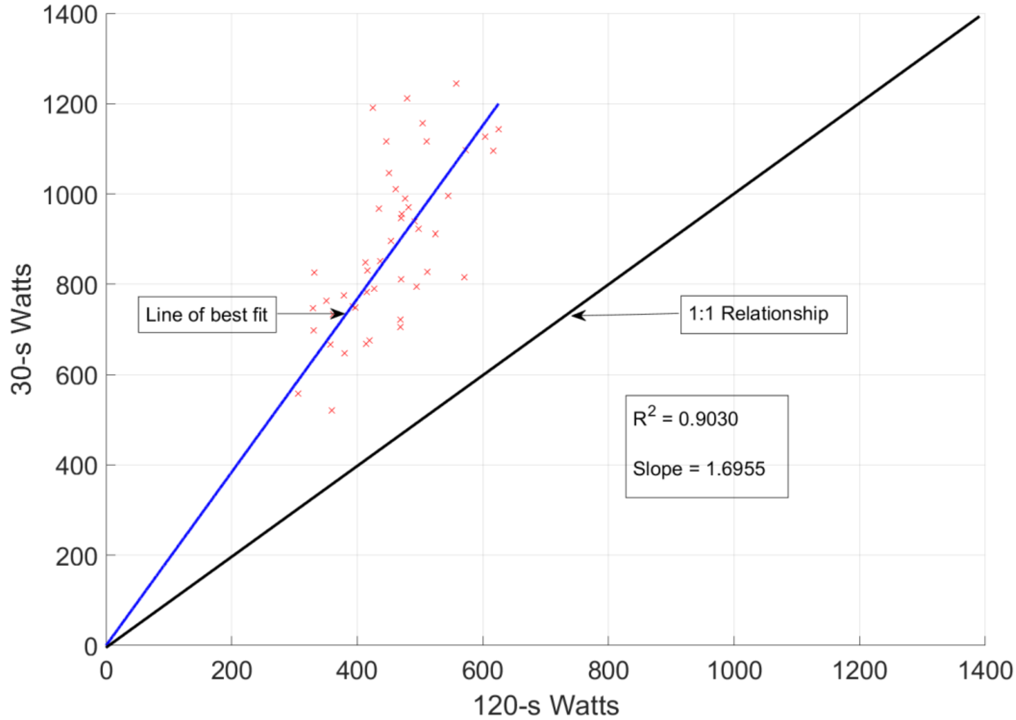


Fig. 6.2: Illustrating the relationship between 30-s power and 120-s power, which provides the line of best fit which can be used to make training decisions. The line illustrating a 1:1 relationship between 30-s and 120-s power is also displayed.

The study in this chapter qualitatively evaluates and then quantifies the training effectiveness of a 3-month training period leading into a main competitive event. In particular, the training of both race winning speed and event winning capacity is tracked, and narrative is used to assess how effective the training was to develop both these outcomes. More specifically, in Ferguson et al. [315], the slope of the line of best fit for a group of sprint cyclists, also shown in Figures 6.1-6.2, provides a good base for assessing whether a rider needs to develop speed or 15-s power, such as when they are below the line, or to develop capacity when they are above the line. Riders close to the line could seek to develop both. With this approach, training is modified based on their balance of capacity and peak power.

For the three training blocks in this study, it is hypothesized:

- **A.** Riders performing below the line should (first) train up for greatest gains in the ability to deliver power, then train over in phase 2, before up again before the key event.
- **B.** Riders performing above the line of best fit should (first) train over (towards the line) for capacity to increase their ability to sustain their higher levels sprint power for longer durations, and multiple rounds in an event.

Together, they create a training and monitoring approach "training towards the line" to track the evolution of performance and simultaneously adapt training based on measured, performance related power metrics.

6.2 Methods

6.2.1 Data Access and Use

All methods were approved under the University of Canterbury, Christchurch, New Zealand Human Research Ethics Committee gave exemption approval for publicly available data (2022/06/EX). This study relied on the open source Strava website to identify and analyze data. Data were downloaded from the Strava app according to the Strava Privacy Policy (https://www.strava.com/legal/privacy) and no personal information was taken from the Strava site.

6.2.2 Overview

From Ferguson et al. [361], 56 sets (44 Male, 12 Female) were found, and examined to determine if there was firstly, 12 weeks of training and racing power meter data. From here the 12-week period was broken into 3 x 4-week blocks, and again the data was examined to determine if there was sufficient maximal 30-s and 120-s power meter measured efforts. From this examination, 25 datasets were found (all male) of sufficient length (12 weeks or longer), and enough data in each of the 3 x 4-week blocks to proceed with the analysis.

All data were obtained from Strava, as previously stated. The use of a single open-source site ensures all data were stored similarly, and any computations used similar data structures and density. The Sauce extension, https://www.sauce.llc/, was then used to download a *.tcx format file containing power meter data for each set of rider files from competition and training sessions for 3-12 months prior to and including either a NZ Championship or World Master's Championship event. Athletes were identified as sprinters based on results from national championships result. From these data, the peak power for two durations over 3 x 4-week blocks of training leading towards a peak performance was identified. Data were plotted on a chart with a line of best fit taken from Ferguson et al. [315]. For each dataset used, narration is provided based on the progression to the key event and the progress made in appendix 6.1.

From the data on Strava peak 30-s and 2-min power were identified over a 12-week period leading into an event, or performance challenge. A total of twenty-five datasets with 12-weeks of continuous training were eventually analyzed. These 12-weeks were then broken into 3 x 4-week blocks to reflect a general periodized process to peak, where the highest 30-s and 2-min peak power outputs should be achieved in the final block.

Peak 30-s power was chosen as this value reflects sprint cycling power from a wide variety of sprint events, while 120-s power was chosen as a power output reflecting sustained performance, for sprint cyclists. The 120-s duration was also used because of the high likelihood of a sprint cyclist doing a maximal effort of this duration in each block. It is also a good measure of capacity for a sprint cyclist [265].

6.2.3 Data analysis

Data were plotted in Matlab R2023b (The MathWorks, Natick, MA) and the slope of 30-s and 120-s was added to the plot to compare data from Ferguson et al. [315]. Jamovi 2.4.2 (Jamovi, Sydney, Australia) was used to illustrate the differences between the progression in the three groups. Results detail the peak power for each block and narration for each dataset is provided to differentiate between a substantial improvement in 30-s power (200-watts or greater), a moderate increase (100-200 watts), and a small increase in 30-s power (less than 100-watts).

6.3 Results

Fig. 6.3 is a histogram showing the differences between large, medium, and small progressions between block 1 and block 3 in the 12-week period. Table 6.1 is the ANOVA analysis which describes the differences for the three groups, and Table 6.1 is the Games Howell post hoc test showing the differences within the three groups. Fig. 6.3, and Table's 6.1-6.2 validate the differences between the three groups.

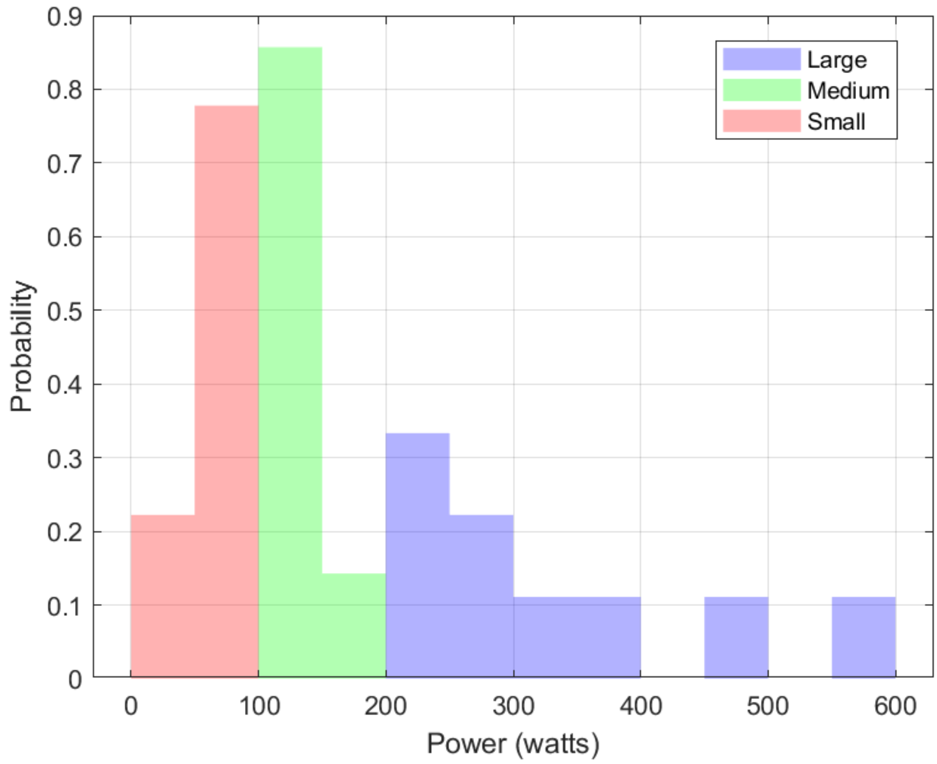


Fig. 6.3: Histogram illustrating differences between the small, medium and large progressions in sprint performance between block 1 and block 3.

Table 6.1: ANOVA to illustrate the differences between the three groups.

One-Way ANOVA (Welch's)

	F	df1	df2	p
Dif Blk1-Blk3	32.0	2	13.5	< .001

Table 6.2: Games – Howell Post Hoc

		Big	Medium	Small
Big	Mean difference	—	-209	-267.2
	p-value	—	0.002	< .001
Medium	Mean difference		—	-58.0
	p-value		—	< .001
Small	Mean difference			—
	p-value			—

The key finding was the different rider-specific evolutions towards a peak 30-s power for a key event, which showed distinct patterns despite all twenty-five datasets focused on performance in sprint, Keirin, team sprint and 500/1000 metre time trial events. Fig. 6.4 shows progressions for all twenty-five riders over the three months (12-weeks) towards a peak 30-s power, reflective of sprint performance over all events. Also plotted in Fig. 6.4, is the slope line of best fit from Ferguson et al. [361] for 30-s and 2-min power for sprint cyclists. All rider-specific trajectories of 30-s and 120-s power evolve around this line during the 3x4-week blocks.

The lines in Fig. 6.4 are color coded by the amount of improvement seen over the study. Fig. 6.5 breaks down Fig. 6.4 into the three classifications of 30-s power gains to highlight the improvements from large to small and clarify where they sit around the line of best fit. Appendix 6.1 narrates all these improvements for each rider specifically.

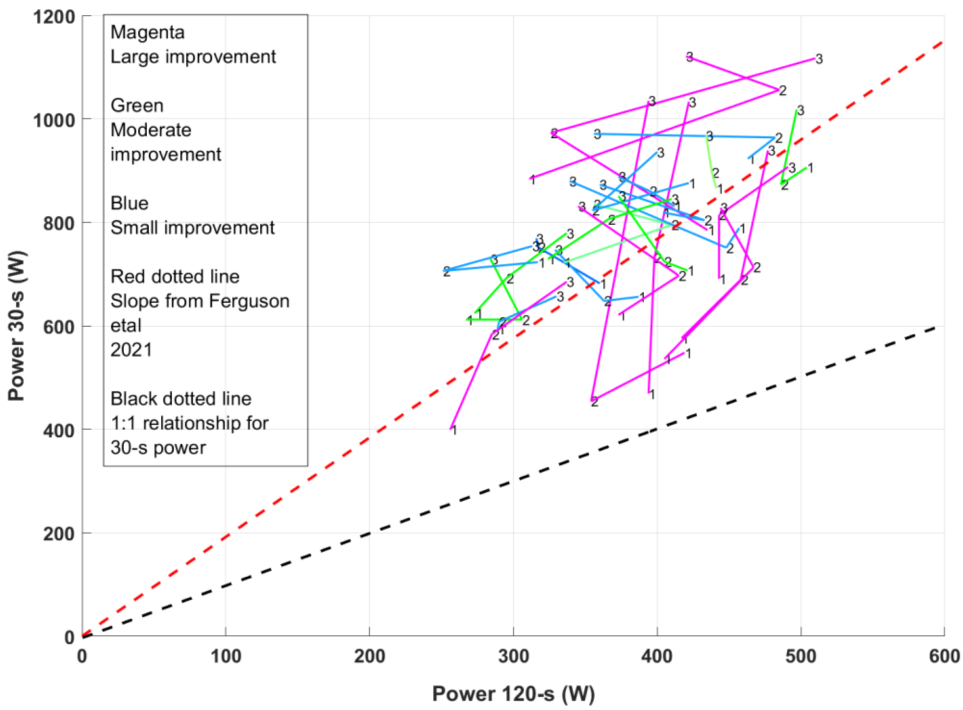
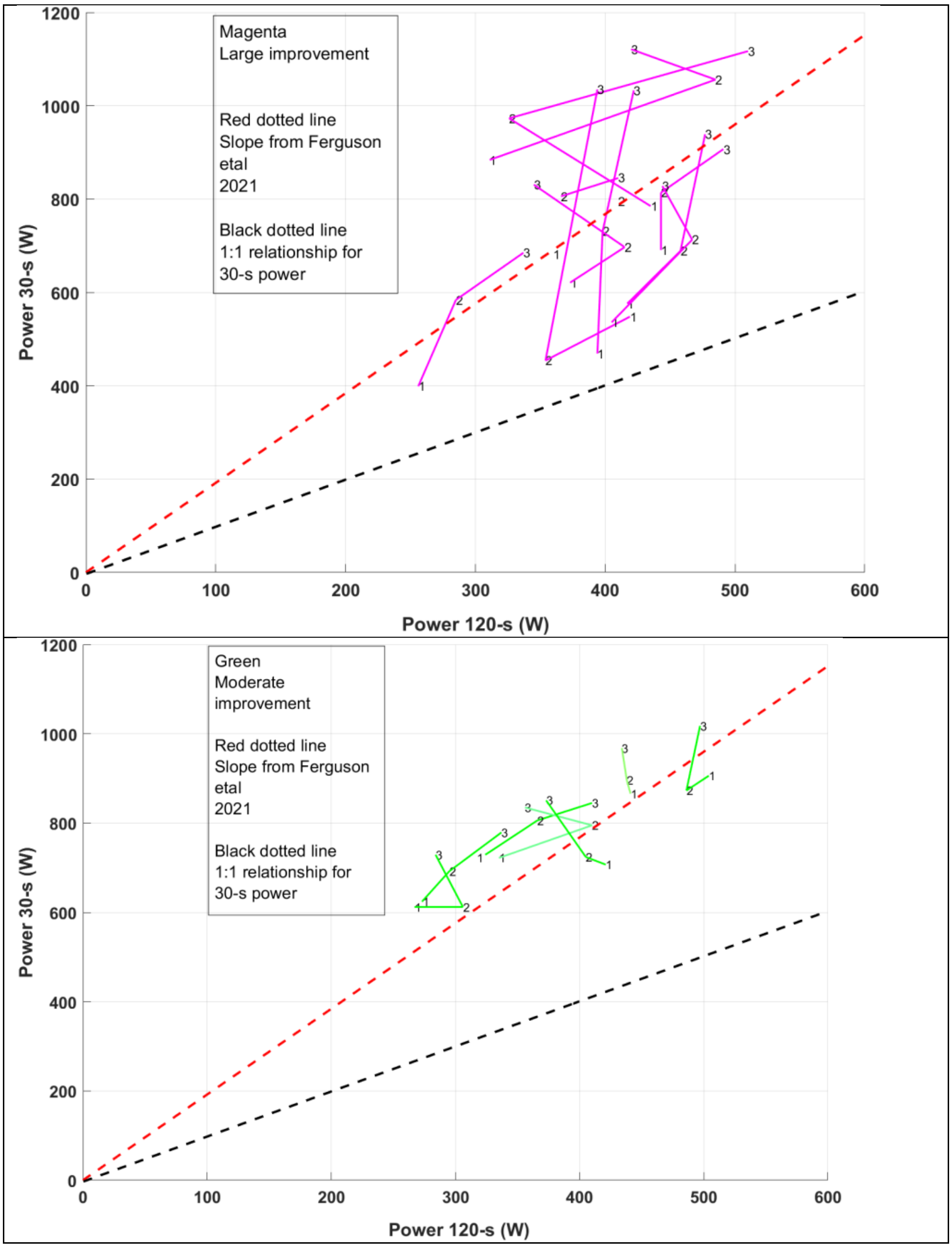


Fig. 6.4: 30-s and 120-s power for all 25 datasets with the progression from block 1, to 2 to 3. The red dashed line is the slope of the line for 30s and 120-s power data for sprinters from Ferguson et al 2021. Black dashed line is the 1:1 relationship between 30-s power.

The lines in Fig. 6.4 are color coded by the amount of improvement seen over the study. Fig. 6.5 breaks down Fig. 6.4 into the three classifications of 30-s power gains to highlight the improvements from large to small and clarify where they sit around the line of best fit. Appendix 6.1 narrates all these improvements for each rider in specific.



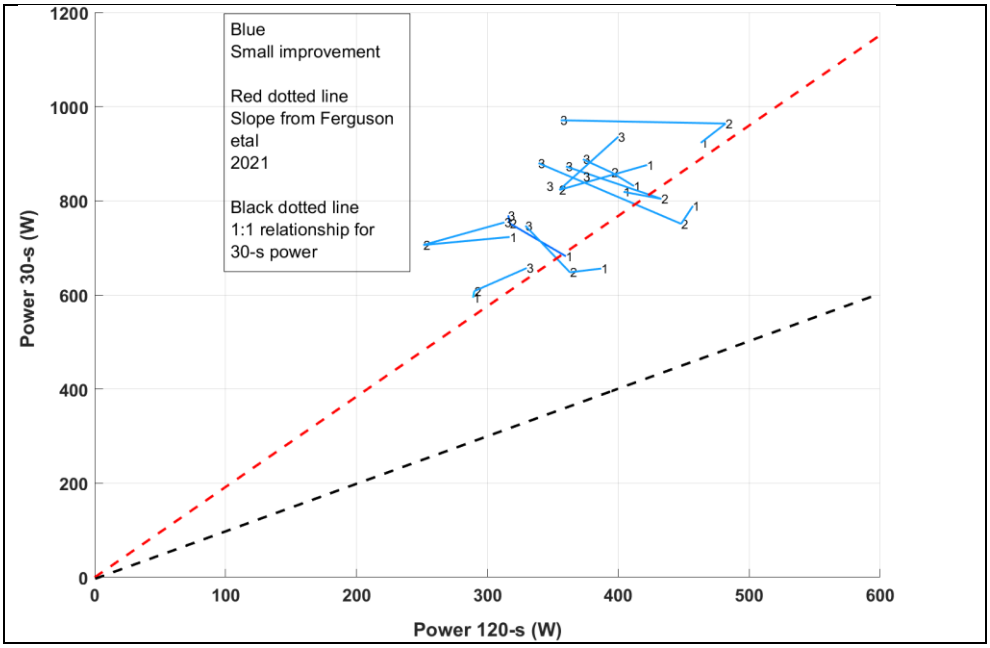


Fig. 6.5: Fig. 6.4, broken into top, magenta: large improvements, middle, green: moderate improvement, and bottom, blue: small improvement.

6.4 Discussion

The main aim of this research is to narrate the progress of sprint cycling athletes as they build towards a peak power performance in 30-s power and use the qualified results and narration to evaluate outcomes in terms of the hypotheses given. Fig. 6.3 and Tables 6.1 and 6.2, all assure three distinct groups. In narrating the differences between large, moderate, and small improvements, those cyclists who showed the greatest improvement in 3-s power were below the line of best fit having greater capacity than peak power in block 1, and/or even block 2, before pushing above the line focusing on higher power. Athletes with moderate or low improvements in power tended to start above the line, and those who saw small improvements in performance typically started well above the line. These cases show riders with a greater balance towards peak power over capacity in block 1. However, for those latter riders, a focus on capacity first and pushing towards power in the third block appears the optimal strategy.

Compared to Wiseman [219], describing a national team building towards an Olympic Championships, where increases in 4-s power throughout the training cycle were reflected with poor performances in a key event. Athletes with the best improvements in this study, went from being strong on capacity, reflected in a better balance between their 30-s and 120-s power, where they were on or below the line of best fit. They also built towards being stronger in race winning power, as they got closer to a key event. A similar approach in 6 high performance sprinters is observed, where the balance of low intensity training (for recovery and capacity) is reduced, and leading into key events the volume of race winning power training is increased [57]. When discussing the two common approaches of short to long and long to short [225], the data suggests the long to short approach was more common in those who achieved big improvements in performance, where the approach also tends to match the main hypotheses for most athletes in this study.

Likely reasons for the differences observed between the groups, was a focus on peak power training over capacity. However, no sprint event is a one-off ride, and each event requires a fine balance between race winning speed and the capacity to both recover quickly and repeat race winning power in subsequent rounds. Thus, as discussed in Chapters 3-4, a mixed approach is likely to deliver better results.

Data points below the line suggest a sprint cyclist who should focus on building their speed by pushing up towards the line of best fit. However, riders above this line should aim to build their short-term endurance capacity, by pushing across (right) towards the line, effectively aiming to hold the speed they have and hold it for longer durations, before pushing peak power in latter training phases. The results presented indicate focusing on training towards this line of best fit, whether starting above or below, or being above or below at the end of any 4-week block, would be the optimal training approach for each individual athlete. For each dataset narration of their individual progression towards a peak performance in this context is made and described in full in Appendix 6.1.

6.4.1 Practical Applications and Coaching Implications

This paper offers coaches and trainers options to enhance their coaching and planning of performance while taking a balanced and measurable / quantified approach to preparing track sprint cyclists, with progress monitored in each phase. This qualified approach allows the coach more options to ensure variety, engagement, and enjoyment in the program. Coaches can now utilize new knowledge to ascertain if the athlete is speed strong or capacity strong and use the early blocks to build more balance in the athlete. Those sprint cyclists who can train more for capacity and entertain racing in longer events on the track in the early blocks building towards training for specific power required in competition. Finally, in terms of goal setting the approach allows multiple targets for the athletes to chase rather than just a peak power Fig. bearing little relation to overall performance in sprint cycling competition.

In practice, those athletes in the large improvement group were below the line focused on capacity, and then in block 2 they pushed a little above the line, focusing on 30-s power and maintaining 2-min power, before focusing on the 30-s power in the final block. The early focus on capacity did not limit their sprint winning power by the end of the block and may have enhanced it. This potential limitation, has been a main reservation of coaches when prescribing training for sprint cyclists [34].

While this study has focused on sprinters, the same principles should apply to track endurance and road cycling. The same principles would apply, using race winning speed and power relative to each event, where these trade-offs are shown in [361], and are similar for male and female riders [362]. A pursuit, balancing speed to race 2-4 kilometers, and the endurance required to race a qualifying heat, recover fast for a final, and have the fitness to withstand a large volume of training.

6.4.2 Limitations and Impact

Limitations of these data are the athletes were of a national level and are already more likely to be doing a wide variety of track cycling events, and even some level of road cycling. However, some participants achieved master's world championship level performances, or U19 level national records. None of the riders used in this study regressed in their power leading into a key competition.

This last point is interesting, as these riders made significant power gains from mixed and capacity focused training, when the current common convention in sprint-training, is targeting peak power all season long [320]. In particular, in this study, peak performers, achieving the highest in 30-s power, made the biggest progression in power, effectively employing a *long too short* approach [225], and a more conventional periodized approach to training, preparation, and competition phase's [363]. As mentioned in the methods, the selection of data excluded any females from the analysis, where Ferguson et al. [362] showed greater variation in power in females compared with men, in sprint cyclists.

Future research should use aim to use larger groups of participants. Research should be done with international athletes, in an early non-Olympic year to ascertain potential improvements to the coaching process and track the progression of female sprint cyclists.

6.5 Summary

This narrative review of 25 datasets of riders preparing towards peak performance shows those athletes who start the process 12 weeks out from a peak performance from a position of strong capacity are able to make bigger improvements in the final block. This provides coaches with a tool to monitor the training status of an athlete as they build towards peak performance. And the means to use the tool to guide the training to guide speed dominant sprinter to build more capacity and the capacity strong rider to build more speed.

Appendix 6.1: Training narrative for everyone:

All cyclists used for this study were known to the lead researcher, hence the ability to narrate the approach they used to achieve their performances in each season. The table is color coded to match the power gain achieved via subjects as shown in Figures 6.3-6.4.

1	Male	18	This is a progression of the rider towards a national event, combined with a relocation to a new area, and started working so training was constrained. He started well below the line at the conclusion of block 1, was closer up towards the line after block 2, and with settling into his new setting was able to push well ahead of the line to make a large increase in 30-s compared to block 1.
2	Male	17	In this progression the rider is building towards an Oceania championship coming off winter training and limited riding on a velodrome. After block 1 they are below the line, after block 2 are still below the line, however with improving weather and access to an outdoor track and a motorbike to provide motorpacing the rider was able to produce a large increase in 30-s power, pushing above the line.
3	Male	17	U19 athlete training for a regional championship. Rider mixing commitments in school’s road cycling with sprint cycling saw them start below the line, move upwards parallel to the line before in the final block being able to focus on sprint cycling to push above the line and achieve good performances in the regional championship.

4	Male	18	This is the progression of a rider towards a regional event, where he successfully broke a U19 national record for the flying 200-m as well as competing in a 1000-m TT, sprint and Keirin series. He starts below the line, moves well above the line after the first block and proceeds to train towards the line in block 2 to finish closer towards the line and achieve a top performance.
5	Male	16	U17 athlete mixing their focus on sprint, track endurance and road cycling events. Stayed below the line the whole time and their performances in all three branches of cycling achieved mixed results.
6	Male	55	Master's athlete training towards a test camp with a reluctance to do actual competition due to previous crashes. This training approach does allow a level of constancy, but no competition is likely to not draw the best out of the rider. They start below the line and push above the line and up and further away from the line in the third block.
7	Male	26	This is a rider training towards a National Championship. All 3 block are performed above the line and the rider produces good 30-s power but struggled in competition to sustain this power over a series, and even within certain rides if pacing was poor (too fast at start) or was forced into a long sprint. To be better prepared for all competition possibilities they need to train more capacity.
8	Male	17	U19 athlete preparing for a national championship. All numbers were below the line as the rider was racing in the sprint events but had a mixed focus looking towards road cycling events beyond the track championship. This approach led to average performances at the national championships.
9	Male	55	Master's athlete training towards a test camp with a reluctance to do actual competition due to previous crashes. This training approach does allow a level of constancy, but no competition is likely to not draw the best out of the rider. They started below the line, moved up parallel to the line and pushed up and above the line in block 3.
10	Male	50	Master's athlete building to an open national championship riding the 1000-m TT, sprint qualifying and round 1 of the sprints. Rider starts above the line and progresses upwards running parallel with the line.

11	Male	16	U19 athlete preparing for a national championship. Started below the line and proceeded above the line in block 2 and made further progress in block 3. This progression was reflected in performances at the national championship.
12	Male	49	This is a masters rider training towards an open event where he rides a 1000-m time trial and a flying 200-m. Did not qualify in the flying 200-m to move into the sprint rounds. Rider is above the line for all three blocks. Indicating they needed more capacity work to lay the foundation for a better all-round performance.
13	Male	45	Master's athlete building to a World Championship in their 5-year age group. Rider above the line for all three blocks. Suffering a back injury so efforts tempered at time. Moderate gains were made. Time was not good relative to previous performance, however with good tactical racing two medals were achieved.
14	Male	42	Master's athlete building to a National Championship. Athlete stayed above the line. In block 2 pushed closer to the line and in block 3 away from the line, not achieving a big increase in power. Results were good at the national championship, however rider relied more on tactics than speed.
15	Male	17	In this progression, after block 1 the rider is below the line and in block two moves downward alongside the line. In block 3 the rider is able to push above the line and achieve good power to win an U19 national sprint title.
16	Male	42	Master's athlete building to a World Championship in their 5 year age group. Rider above the line for all blocks pushing up and away from the line slightly. Medal won at the Championship, but not the fastest times recorded.
17	Male	17	U19 cyclist competing at a national championship in their grade. Rider below the line and pushed closer below the line before moving over the line and upwards. This move from capacity to more power for competition was matched with good results for this rider medaling in the U19 sprint event.
18	Male	43	Master's athlete building to a National Championship. Athlete stayed above the line. Rider started below the line and moved closer to the line in block 2 then made a large push for power in the third block. A large increase in sprint power was not realized and performances were reflected in this.

19	Male	49	Master's athlete training for open competition 1000-m TT and sprint qualifying. Starts just below the line and makes a big push above the line and makes little progress in the final block suggesting a more balanced approach to building sprint power and sprint capacity.
20	Male	50	Master's rider preparing for a open competition riding the 1000-m TT and sprint qualifying. Above the line for all blocks, little gain between block 1 and 2, but better gain in block three. Athlete suffering from back injury.
21	Male	44	Master's athlete building to a National Championship. Athlete stayed above the line. Rider was above the line for all three blocks pushing away from the line in block 2 and while trying to refocus on capacity did not gain much power. However, results were excellent for this event.
22	Male	42	Master's cyclist building towards a regional championship racing sprint and endurance events. Athlete started below the line and made a big push for power in block 2 with regular carnival racing but was able to perform more mixed training which saw them move back towards the line and achieve good power at the regional championship.
23	Male	43	Master's cyclist building towards a regional championship racing sprint and endurance events. Rider started above the line, made a big push for capacity in block 2 before pushing for power in block 3 achieving good sprint performances and average endurance performances.
24	Male	48	Master's cyclists building towards a world championship in his 5 year age group. All blocks above the line and block 2 moved closer to the line, however a big push to deliver more power mean a large move away from the line and minimal gain in power, reflected in average performances at the world championships.
25	Male	50	Master's rider competing in their 5 year age band at a World Championship. Riding the 500-m TT and match sprint series achieving 4 rides before being eliminated. Athlete suffering from back injury. Athlete makes a big push for power from block 1-2 and this, plus injury, means there is not a large gain in power in the final block.

Chapter 7: Sprint cycling power duration curve: Linear, anaerobic power reserve and critical power compared.

7.1 Introduction

Sprint cycling competition is a branch of track cycling based around three Olympic events, the Keirin, the match sprint, and the team sprint, plus a world championship event, the 500-m (female) and 1000-m time trial (male). In 2025 the women's distance will change to 1000-m [34]. All events require a balance of delivering the highest power outputs observed in the sport, alongside BMX cycle races [364]. Sprinting also requires maintaining this balance across several rounds of an event to make a medal final, and for many athletes, to accomplish these tasks across the 3-4 different events within a championship meet [34]. The main challenge for a coach and sport scientist is developing performance models, to develop and guide general coaching practice and methods. Within sprint cycling coaching there is the potential to make programs personalized, and thus customized or made specific to each individual athlete.

In sprint cycling, most of the models are based on athlete testing, and usually on a narrow spectrum of the power-duration curve [320]. This narrow approach can lead to a myopic view of the sport and poor choices in general coaching and training decisions for a specific athlete [219]. This study proposes a wider view of the power around the common durations of sprint cycling: 15 – 30 seconds.

The use of the Wingate test, a commonly 30-s, all out test is often used to assess sprint cyclists to determine peak power, time to peak power, power at the end of the test, average power for test duration and from the peak and average power a fatigue index can be calculated [167]. Challenges with the use of the Wingate test are the all-out nature of the test not reflecting the way sprints are raced, and the focus on the peak power component rather than the average power, which was the original intent of the test [365, 366]. In addition, Wingate testing interrupts training due to its all-out nature, and thus is not a repetitive test for use with monitoring an athlete's training or condition.

With the introduction of bicycle based ergometers, coaches and sport scientists have been able to record power output in the field, measured in watts [168]. In a much similar way to the Wingate test, the use of power meters was used to make individual recordings, such as power itself, or power in relation to body weight, or frontal area [184], without attempting to develop a model to try and tie the main predictors of sprint cycling performance together. However, as with the Wingate test, power meter data has come to be seen as a result in itself and a training metric of choice for some.

The critical power model was initially used to describe the power an athlete can sustain for a long time [367]. This model has evolved to describe the power output separating the heavy and severe exercise domains, which have a claimed relationship with the maximal metabolic steady state (MMSS) [305]. While the MMSS is more relevant to endurance performance, the determination of CP also delivers an estimate of high intensity energy in kilojoules, referred to as *W'* [368]. This part of the CP calculation may be of use to the modelling of sprint cycling performance, but also has limitations.

In track and field, the anaerobic speed reserve was proposed to model performance of efforts between 1-s and 300-s in lieu of challenges in correctly measuring the energetics of sprint and middle distance running [359]. The model is based on maximal sprint speed, maximal aerobic speed and a coefficient claiming to be an accurate method of predicting sprint running performance [325]. This concept has been applied to road cycling sprint performance, referred to as the anaerobic power reserve [266, 267].

The study in this chapter examines both the critical power *W'* component and the anaerobic power reserve (APR) in relation to a variety of durations around the common sprint cycling durations of 15-30 seconds. The following hypothesizes are evaluated:

A. *W'* and APR model of sprint cycling power being a linear model

B. The relationship with sprint cycling power-duration curve

7.2 Methods

7.2.1 Study Design

Publicly available power meter data from a cohort of national level cyclists was used for study. The data was taken from the Strava website according to the Strava Privacy Policy (https://www.strava.com/legal), and the Sauce web browser extension (https://www.sauce.llc) to download a *.tcx file. This data was downloaded to the WKO5 (TrainingPeaks, Boulder, CO) power meter analysis software to determine power duration data for each cyclist. This data was then added to a spreadsheet and analyzed in either Matlab to measure the relationships.

7.2.2 Participants

Table 7.1 summarizes the participant data for the study. A total of 27 sprint cyclists supplied 56 datasets with some participants data located from several different seasons. From the Strava data it is possible to determine their age and weight. The same data set was used in Ferguson et al. [361], where the sprint cycling group was assured by comparison to a group of track endurance cyclists. Because of the public accessibility of data on the publicly available Strava website the University of Canterbury Human Research Ethics Committee exempted this study from seeking ethics approval (2022/06/EX).

Table 7.1: Participant data including this study, endurance (END) cyclists. Median and interquartile range [IQR].

	All	Male	Female
Data Sets	56	44	12
Participants	27	21	6
Age (years)	19 [16 - 39]	25 [16 - 40]	17 [16 - 19]
Weight (kg)	76.5 [74.0 - 86.8]	80.3 [75.0 - 88.0]	64.0 [60.0 - 74.0]

7.2.3 Models Used

1. Linear relationship starting through the 0.0 power point (Chapters 3 - 5):

   $$15/30 \text{ second Watts} = (a0 \cdot x)$$

   Where *a0* is the constant coefficients found by identifying the best function for each case from the measured data, and x = *duration.*

2. Anaerobic Power Reserve [267]:

   $$P_{(t)} = P_{(3-min)} + (P_{(max)} - P_{(3-min)}) \times e^{(-k \times t)}$$

   Where P = power in watts, t = time in seconds, $P_{(3\text{-}min)}$ = 3-min power in watts, $P_{(max)}$ = 1-s power, e = base of natural logarithm (2.1718), ^{k} constant rate of exponential decline (0.0277) based on Sanders [267].

3. 2-Parameter Critical Power (CP) Model [329]:

$$P_{(t)}=\frac{W\prime}{t}+CP$$

Where *W'* = work in kilojoules above critical power, and *CP* = Critical Power. For this study, four time durations of 2, 4, 8 and 20-min were used to find CP and *W'*.

4. W' model [369].

$$W' = A + B \times T_{lim}$$

W' = limit of work (joules), A = a fixed energy reserve (J), B = critical power (W), and T_{lim} = time limit (s).

Models 2 and 3 are the APR and CP model, where model 4, the *W'* value of CP is a third model for comparison to the linear relationship model at various durations.

7.2.4 Analyses

All models were assessed using Matlab version 2023a (The MathWorks Natick MA). The linear model assumes a linear relationship through the zero-power point (0,0). The (0,0) point acknowledges all energetic pathways are functioning at a given time, and both start at point 0. The model coefficients are identified using total least squares [311, 312] because there is test variability and error in both the *x* (power over 1-s to 20-min) and *y* axis (sprint power over 15 and 30 seconds) measured power output metrics.

In particular, the CP and APR models, as well as the derived *W'* metric from the CP model, are compared to the linear relationship model. The goal is to show the APR, CP and *W'* models do not reflect performance for sprint cyclists, as well as the linear models presented in this thesis. Since the APR and CP models both use 1–3-min durations it might be assumed they would better represent this cohort, as hypothesized.

7.3 Results

Table 7.2 shows the R^2 a slope for all the four models for 1-s, 5-s, 15-s, 30-s, 60-s, 2-min, and 3-min power. Fig. 7.1 shows the R^2 for all five models and all durations. Fig. 7.2 shows the slopes for all five models and all durations.

Table 7.2: R^2 and slope for all five models.

Time		15-s Power	30-s Power	APR	CP	*W'*
1-s	R^2	0.96	0.90	0.99	0.97	0.99
	Slope	0.76	0.58	0.88	0.17	0.018
5-s	R^2	0.97	0.92	0.99	0.96	0.99
	Slope	0.83	0.65	0.91	0.19	0.024
15-s	R^2	**1.00**	0.95	0.97	0.94	0.99
	Slope	**1.00**	0.78	0.91	0.25	0.024
30-s	R^2	0.95	**1.00**	0.92	0.92	0.99
	Slope	1.30	**1.00**	0.95	0.30	0.033
45-s	R^2	0.94	0.96	0.92	0.88	0.98
	Slope	1.58	1.23	0.96	0.39	0.040
60-s	R^2	0.94	0.94	0.93	0.88	0.98
	Slope	1.83	1.42	0.96	0.44	0.049
2-min	R^2	0.92	0.92	0.96	0.84	0.95
	Slope	2.45	1.91	0.98	0.59	0.065
3-min	R^2	0.91	0.90	0.99	0.86	0.95
	Slope	2.65	2.10	1.02	0.66	0.069

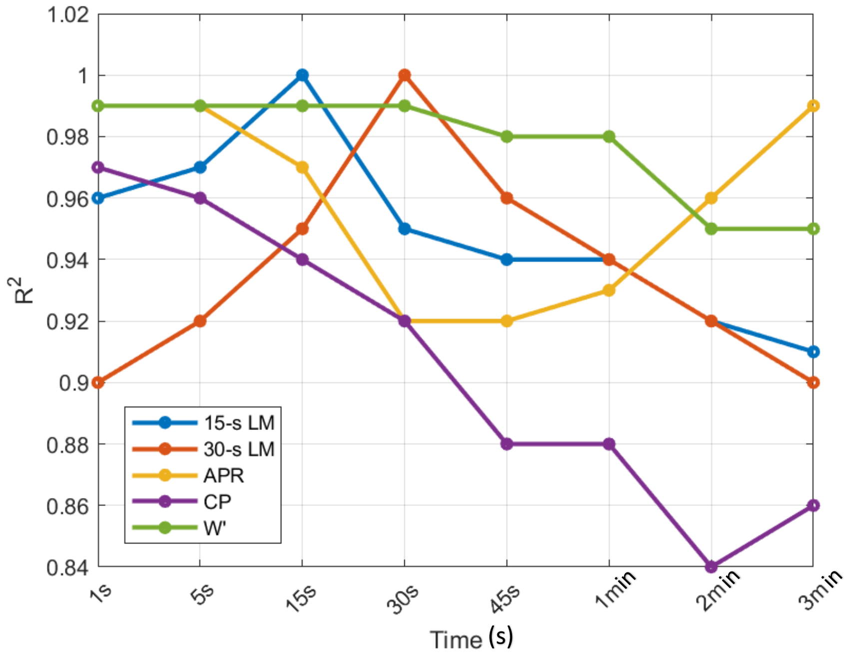


Fig. 7.1: R^2 and for all 5 models over all the durations

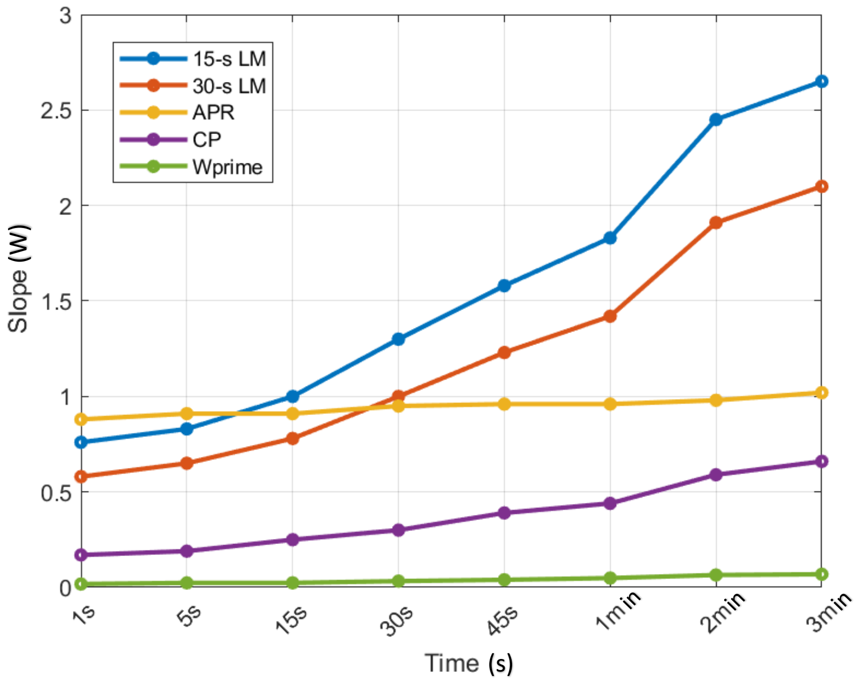


Fig. 7.2: Slopes for all 5 models over all durations

7.4 Discussion

The aim of this study was to compare three different models (and two components of critical power) with several durations around sprint cycling. As found in three of Ferguson et al's. studies [315, 361, 362], the best relationships were for 15 and 30 second power, showing the best predictors of 15-30s power was, unsurprisingly the 15-30 second power itself. This has implications for the testing of sprint cyclists, guiding how they need to train for sprint competition. Therefore, although the first hypothesis has proven accurate and the linear model is superior among the models studied, the second hypothesis remains uncertain at most.

7.4.1 Total Least Squares (Linear) Model for 15-s Power

Table 7.2 and Fig. 7.1 show the R^2 for 15-s power using the total least squares for 15-s was started high for 1-s and rose to the closest point, outside of the 15-s 1:1 relationship, at 5-s and past 15-s dropped consistently, while still remaining high out to 3-min. This result is consistent with the findings of Ferguson et al where R^2 stayed high all the way out to 20-min [361]. In particular, it shows the power duration relationship is parabolic with the highest relationships around event specific power output remaining relatively high over all durations. Table 7.2 and Fig. 7.2 show the slope for the model consistently moves away from the 1:1 perfect relationship (slope of 1.0) as duration shifts either way from the 15-s duration replicating the short sprint in a match race or the rider 1 in a Team Sprint.

7.4.2 Total Least Squares (Linear) Model for 30-s Power

While 15-s power is indicative of the short sprints of track cycling, 30-s is more reflective of the longer sprints using a larger gear ratio. For example, the Keirin, where racing starts with the motorbike pulling off with 750-m to go and rider 2 in team sprint riding 500-m. As a result, Fig. 7.1 shows a stronger parabolic power duration relationship using the total least squares model for 30-s. 1-s and 5-s R^2 were lower than 15-s to 2-min power, and the claimed 1-s gold standard power duration had as strong a relationship to 30-s power as 3-min power, which indicates it is nowhere near a gold standard for sprint duration performance. Again, Fig. 7.2 shows the slope of all durations in this study. All slopes have an impact on 30-s performance, and suggest preparation for 30-s performance should mainly incorporate 30-s efforts, but will also measurably benefit from including efforts, based off this study, from 1-s to 3-min, and based on the results from two Ferguson et al. studies, will also benefit similarly from efforts up to 20-min, albeit with somewhat decreasing returns [315, 361].

7.4.3 Anaerobic Power Reserve (APR)

Interestingly, this model showed an inverse parabola, as shown in Fig. 7.1, around the relations with each duration. This relationship is possibly a function of the model using the specific duration for each power duration [267]. The drop off in R^2 from 1-s to 30-60 seconds, and then rise back towards 3-min APR potentially reflects how the model uses only 1-s and 180-s power in its calculation, thus deliberately excluding the sprint race durations. The slope in Fig. 7.2 is consistent throughout each duration while both total least squares models and the CP model rise as the power increases from 15-30 second power. The slopes depicted in Fig. 7.2 extend only up to their maximum duration of 3 mins, displaying a level curve. This contrasts significantly with previous research, experimentation, and the behavior of the alternative models.

7.4.4 Critical Power (CP)

The asymptote component of the critical power model was not expected to hold a high relationships with power from the extreme exercise domain [329]. Surprisingly, the R^2 value in Table 7.2 was high for the shortest durations. However, this value dropped to levels well below all other models from the 30-s duration onwards. The slope in Fig. 7.2 was more indicative of the bias of the model towards longer duration measures, gradually pushing closer towards the 1:1 relationship as the duration rose to 3-min. The gradients displayed in Fig. 7.2 pertaining to this specific parameter of the CP model are notably gentle, lacking any substantial deviation from the anticipated physiological parabolic pattern. As a result, the practical usefulness of this parameter is constrained.

7.4.5 W' Parameter of CP

Fig. 7.1 shows a linear relationship between the *W'* component of the critical power which did taper off again past 60-s power. Fig. 7.2 shows the slope for *W'* shares the same linear curve. Therefore, the model suggests, in sprint cyclists, this value is of some utility, which does have to be weighed against the time it takes to do 2-5 maximal trials to adequately determine CP, and therefore *W'*, which is highly intrusive or interruptive of training.

7.4.6 Observations between the models

The total least square linear models reflect a parabolic relationship in the power-duration curve around the two sprint-cycling competition specific durations of 15-s and 30-s. These models had strong correlations across power with (expected) changes in slope as the differences in duration increased out to 20-min. The model quality was high throughout, which is a further form of model validation and unique to this study, considering the broad range of durations.

The critical power model (CP) is not designed to predict performance in sprint cycling, and this outcome is evident in the results. The anaerobic power reserve (APR) shows an inverse parabolic relationship to the power-duration curve, while *W'* (from the CP model) shows a decreasing relationship along the power duration curve. Both APR and *W'* both reflect issues with the calculation, where APR is calculated from 1-s and 180-s power, and the 2-factor critical power model requires at least two power duration efforts of 2-12 min durations [370], all of which are intrusive, and thus not useful for regular monitoring of training, as well as difficult to perform.

7.4.7 Limitations

One of the limitations of this study is the data set reflects track cycling sprint cyclists at a national level. Higher sprint duration powers would be expected from elite cyclists [156]. However, the nature of elite level sprint cycling is based around the development of peak power [319, 320]. Riders in this study are more likely to perform some endurance events, and thus are more likely to deliver more peak power over longer durations, than an elite rider solely focused on short durations. In Ferguson et al. the sprint group were verified against a track endurance group where there was some crossover around the 60-s duration as seen in Chapters 4 and 5 [361]. In the kilometer time trial, it is common for track endurance cyclists to outperform some sprint cyclists. Despite this crossover at 60-s, there is still a distinct difference in power in the sprint group for 15-30 second power.

This crossover may also affect the calculation of both APR, requiring a 180-s maximal effort, and at least two maximal efforts between 2-12-mins to determine CP and therefore *W'*. Current sprint coaching practice typically discourages efforts longer than 60-s. This specific notion, is directly challenged by the data presented in this study and other research [315, 361].

Similarly, the utilization of openly accessible data guarantees more extensive datasets and the possibility of drawing conclusions with broader applicability. In addition, despite the presence of data fluctuations, as mentioned, the impact of these fluctuations on the studied group can be mitigated through an increase in the number of participants. This improvement is most clear in the outcomes for the linear model, especially in the elevated R^2 values showcasing well-grouped data. This suggests the diversity among riders was not significantly extensive.

7.4.8 Implications

The data confirm previous associations of the power duration curve and a model of sprint cycling performance. The model can be used to assess a rider by using the line of best fit on a scatter plot of a group of sprint cyclists to determine whether a rider is *power strong*, sits above the line of best fit, or *capacity strong*, below the line of best fit, to determine what should be trained, in relation to their strengths and weaknesses, and in relation to where they are, in relation to key events (Chapter 5).

Lastly, an additional coaching implication arises when contemplating the comprehensive linear total least squares modelling of the power duration curve across all timeframes. This approach has the potential to assist coaches in directing holistic training efforts aimed at enhancing the complete power duration curve, thus advancing the overall performance of athletes. This strategy sharply diverges from prevalent coaching approaches centered around individual power levels. However, it becomes feasible through the modelling techniques introduced throughout this thesis and can be readily put into practice using easily accessible power meter data.

7.5 Summary

The total least square 15-s and 30-s best reflected the power duration it was expected to see in competition. The anaerobic power reserve (APR) and critical power *W'* models potentially reflected issues in the calculation of both models, and thus have lower correlation to these race durations. These models should be used to understand the current performance of the rider and help determine whether they should be training to build their peak power, or to improve their capacity to hold their sprint power for longer.

Chapter 8: Power-duration relationships for track pursuit cyclists

8.1 Introduction

Track cycling pursuit events cover distances of 2000-m to 4000-m for individual riders based on age. They are thus a more capacity or endurance focused event compared to the sprint events. From 2025 the sex differences in distance will be removed. These event cyclists thus make a useful comparator to prior chapters on sprint cycling power and performance.

A pursuit race consists of an individual or a team of 4 riders starting on opposite sides of the track, racing with the goal to catch their opponent or record the fastest time for the distance. An individual pursuit has a qualifying round, then a final where the 3rd and 4th qualifiers race for the bronze medal and the top two qualifiers ride for Gold and Silver. The team pursuit may use the same format or have a round 1 where the top 4 teams only can qualify for the Gold-Silver final but the two fastest of the remaining six qualify for the bronze ride. In all cases, just as with multiple rounds for sprint riders, there is also a multiple performance requirement for these events and cyclists.

At an elite level these events all require a mix of peak power and sustained power, and despite the nature of the events, the best performers typically perform a large volume of training [65]. The modelling of performance for track cycling typically revolves around one of tests providing a snapshot of a particular aspect of the track cyclist. Thus, despite the range of power and training durations involved, single or a few narrow-focused tests are used to guide training.

For example, a Wingate test is commonly a 30-s all out test providing peak power, time to peak power, average power, power at test termination (minimal power), and, based from peak and average power, a fatigue index for the test [167]. A longer ramp test is used to make estimates of the maximal metabolic steady state based on either ventilation, lactate [371], and more recently non infrared spectrography [372]. These tests provide a snapshot of claimed thresholds of performance, notably LT1/VT1, the so-called *aerobic threshold*, where lactate increases above resting levels, and LT2/VT2, the so-called *anaerobic threshold*, where ventilation increases, and lactate levels rise rapidly, and performance above this level leads to an athlete achieving their $\dot{V}O2_{max}$ [373].

However, none of these tests cover the complete nature of track cycling endurance competitions. As a result, mathematical models have been proposed. Critical power (CP) is a model of the power – duration curve which gives both an estimate of the LT2/VT2, or what is referred to as the transition from the heavy exercise domain to the severe exercise domain, and examines durations from 1-sec to 3-mins [329]. The anaerobic power reserve (APR) is a model based on the anaerobic speed reserve taken from running based measures of maximal sprint speed and maximal aerobic speed (or speed at the $\dot{V}O2_{max}$) [265]. The APR is a cycling specific variation using 1-s and 180-s to determine the APR, which is used to model performance in durations from 1-300 seconds [266, 267]. Thus, both CP and APR are also used to examine or assess endurance track cyclists, as well as sprint cyclists in Chapter 7.

Ferguson et al. [315, 361] presented studies showing a better model to understand sprint cycling. These studies show a parabolic relationship with power around a duration, and Chapter 7 provides data suggesting the nature of both the CP and APR models may be biased by the inputs to the model used to create them.

This chapter examines the power – duration curve for duration times common to track endurance cycling and using endurance cyclists. The main hypotheses are defined:

A. A total least squares linear model of track cycling endurance power at 1-to-3-min durations is a better model than APR and both the Critical Power for pursuit cyclists across all durations of power measurement from 1-s to 20-min.

B. The APR and CP models may perform better for pursuit cyclists than for sprinters in Chapter 7 given their definition and bias to longer durations.

8.2 Methods

8.2.1 Study Design

Publicly available power meter data was used from a group of national level cyclists according to the Strava Privacy Policy (https://www.strava.com/legal), using the Sauce web browser extension (https://www.sauce.llc) to download a *.tcx file. Data was downloaded to WKO5 (TrainingPeaks, Boulder, CO) software to determine power duration data for each cyclist.

8.2.2 Participants

Table 8.1 summarizes participant data. A total of thirty-four datasets from 15 riders, reflecting periods of pursuit races, track racing, and some road cycling events. Age and weight were determined from Strava data. Due to the public accessibility of data on Strava, the University of Canterbury Human Research Ethics Committee exempted this study from ethics approval (2022/06/EX).

Table 8.1: Participant data presented as median and interquartile range [IQR].

	All	Male	Female
Participants	15	11	4
Data Sets	34	23	11
Age	20.5 [17.0-31.8]	19 [17.0-32.5]	18 [17.5-29.5]
Weight	62 [59.5-63.0]	73 [71.0-76.0]	62 [59.5-63.0]

8.2.3 Models Used

Three models are examined across this cohort:

1. Linear relationship starting through the 0.0 power point (Chapters 3, 4, 5 and & 7):

$$60/120/240 \text{ second Watts} = (a0 \cdot x)$$

Where a0 is the constant coefficients found by identifying the best function for each case from the measured data, and x = duration.

2. Anaerobic Power Reserve [267]:

$$P_{(t)} = P_{(3-min)} + (P_{(max)} - P_{(3-min)}) \times e^{(-k \times t)}$$

Where P = power in watts, t = time in seconds, $P_{(3\text{-}min)}$ = 3-min power in watts, $P_{(max)}$ = 1-s power, e = base of natural logarithm (2.1718), ^{k} constant rate of exponential decline (0.0277) based on Sanders [267].

3. 2-Parameter Critical Power (CP) Model [329]:

$$P_{(t)} = \frac{W'}{t} + CP$$

Where *W'* = work in kilojoules above the critical power, CP = Critical Power. For this study, four time durations of 2-min, 4-min, 8-min and 20-min was used to estimate CP and *W'*.

4. W' model [369].

$W' = A + B \times T_{lim}$

W' = limit of work (joules), A = a fixed energy reserve (J), B = critical power (W), and T_{lim} = time limit (s).

Models 2 and 3 are the APR and CP model, where model four, the *W'* value of CP is a third model for comparison to the linear relationship model at various durations.

8.2.4 Analyses

All models were assessed using Matlab version 2023a (The MathWorks Natick MA). Model 1 assumes a linear relationship through a zero-power point (0,0). The (0,0) point acknowledges all energetic pathways are functioning at a given time, and both start at a value of 0. The model coefficients are identified using total least squares [311, 312] because there is test variability and error in both the *x* (power over 1-s to 20-min) and *y* axis (pursuit power over 1-min, 2-min and 3-min) measured power output metrics.

The CP and APR models, as well as the derived *W'* metric from the CP model, are compared to the linear relationship model of earlier chapters. For pursuit cyclists, unlike the sprinters of Chapter 7, the durations of interest are at the event relevant durations of 1-3 min, rather than 15-s and 30-s durations for track sprint cycling events. Thus, the linear model at 60-s (1-min), 2-min, and 3-min are compared to these three existing models. The goal is to assess whether the APR, CP and *W'* models reflect performance for pursuit cyclists, as well as the linear models presented in this thesis, just as was done for sprint cyclists and durations in Chapter 7. Since the APR and CP models both use 1–3-min durations it might be assumed they would better represent this cohort, as hypothesized.

8.3 Results

Table 8.2 shows the R^2 and slope for each model and all the durations. Fig. 8.1 shows the R^2 values. Fig. 8.2 shows the slopes for each model.

Table 8.2: R^2 and slope for the linear model at 60-s, 2-min, and 3-min power at all durations and the same relationships for the three models of APR, CP and *W'*

Power (watts)		1-min Power	2-min Power	3-min Power	APR	CP	*W'*
5-s	R^2	0.96	0.96	0.97	0.99	0.96	1.00
	Slope	0.49	0.39	0.36	0.89	0.24	0.019
15-s	R^2	0.97	0.97	0.97	0.96	0.95	1.00
	Slope	0.60	0.47	0.43	0.95	0.32	0.027
30-s	R^2	0.97	0.97	0.97	0.96	0.93	0.99
	Slope	0.76	0.61	0.56	0.96	0.41	0.033
45-s	R^2	0.99	0.97	0.98	0.94	0.92	0.99
	Slope	0.91	0.72	0.67	0.99	0.49	0.039
60-s	R^2	**1.00**	0.97	0.97	0.94	0.92	0.99
	Slope	**1.00**	0.82	0.72	0.99	0.54	0.043
2-min	R^2	0.97	**1.00**	0.99	0.98	0.93	0.98
	Slope	1.24	**1.00**	0.93	0.99	0.67	0.054
3-min	R^2	0.97	0.99	**1.00**	1.00	0.94	0.98
	Slope	1.37	1.08	**1.00**	1.01	0.72	0.058
4-min	R^2	0.97	0.98	0.99	0.99	0.95	0.97
	Slope	1.45	1.16	1.06	1.06	0.76	0.060
8-min	R^2	0.95	0.97	0.98		0.95	0.97
	Slope	1.61	1.28	1.18		0.85	0.068
12-min	R^2	0.95	0.96	0.98		0.97	0.96
	Slope	1.67	1.35	1.24		0.89	0.070
20-min	R^2	0.95	0.96	0.97		0.99	0.95
	Slope	0.95	1.45	1.33		0.94	0.074

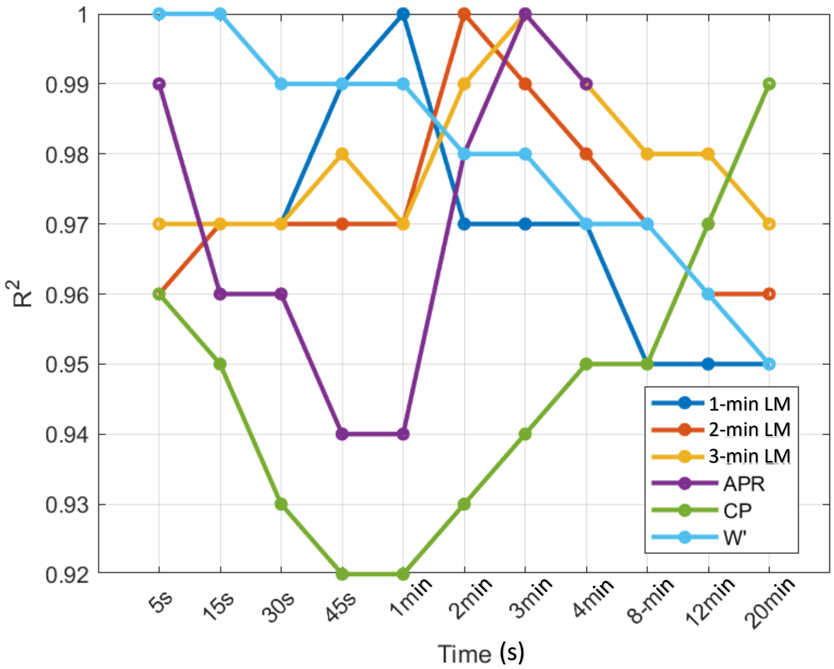


Fig. 8.1: R^2 for all 5 models over all the durations

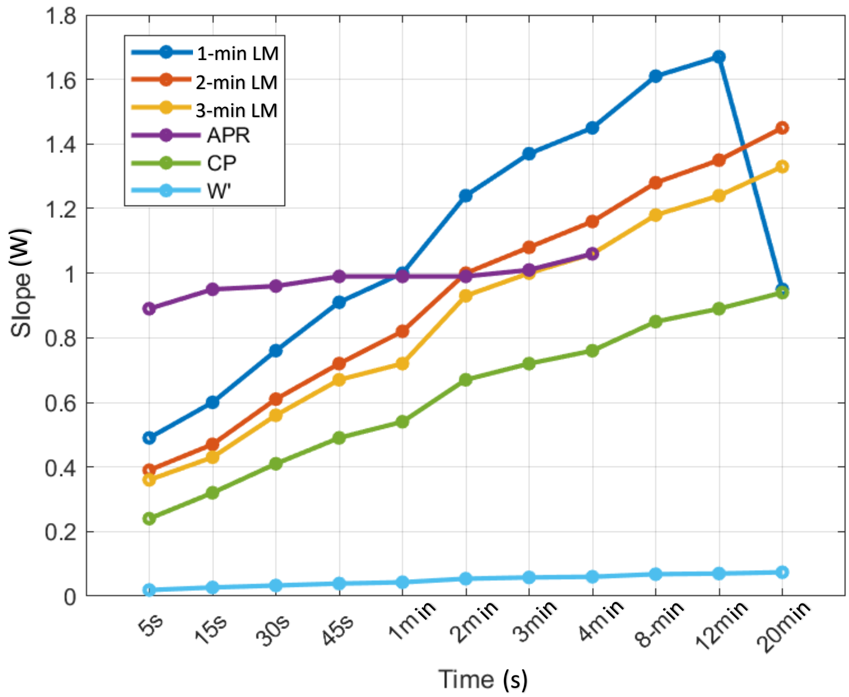


Fig. 8.2: Slopes for all 5 models over all durations

8.4 Discussion

The intent of the study was to compare current APR and CP models, and *W'* from CP, of the to the linear-based models describing the power-duration curve developed and analyzed in Chapters 3, 4, and 7 for pursuit cyclists at pursuit durations of 1-min to 3-min. Both the two-parameter critical power (CP) and anaerobic power reserve (APR) models showed a bias towards the time and power durations used to construct the models, which are within these durations for pursuit cyclists. They are thus, expected to perform better in this comparison than in Chapter 7, at sprint cycling durations. While the first hypothesis held, and the linear model is the best of the models presented, the second hypothesis is inconclusive at best.

8.4.1 The 1-min, 2-min and 3-min Linear Model

As found in Chapter 7, Fig. 8.1 highlighting a parabolic curve for all three models at 60-s, 120-s and 180-s, demonstrating how power in track cycling endurance cycling is not governed by peak power. Table 8.2 shows, for a kilometer time trial rider (approx 60-s), 20-min power is just as related to performance as peak power, and as well as full distance efforts, the data shows the importance of 30-s and 45-s efforts, over other durations. For a rider looking at a 120-s performance, the data suggests they should look at over-distance efforts to build the power needed to perform, as well as specific event duration training. For 180-s power the data suggests training around the 180-s mark with a mix of 120-s and 240-s efforts. The slopes in Fig. 8.2 show a strong parabolic shape for all durations.

8.4.2 Anaerobic Power Reserve Model (APR)

The clearest observation was an inverse parabolic curve based around the 1-s and 180-s power durations, which are the two parameters used to develop the model. This raises questions about the ability of the model to adequately model short durations of performance. Sanders and

Heijboer found similar R^2 and slope metrics for power output and predicted power output in road cycling sprinters who can commonly cross over with track endurance cyclists [374]. They highlighted a large intraindividual difference in APR in riders, and their plots for four different time decay exponents (k) highlighted the bias for 1-s and 180-s power. The slopes in Fig. 8.2 only go out to its maximal 3-min duration, and show a flat curve, which is different from prior literature and testing, and the other models.

8.4.3 Critical Power (CP)

Again, Fig. 8.1 shows an inverse parabolic relationship for 2-parameter critical power was observed. Table 8.2 shows a mean max mean power from the riders was used, rather than 4 dedicated tests of the duration, which can have a biasing effect on determining the critical power, and therefore the *W'* [375]. The slopes in Fig. 8.2 show a good parabolic shape, as might be expected physiologically.

8.4.4 W' Parameter of CP

A linear power-duration relationship with R^2 from 1-s down to 20-min was observed in Fig. 8.1, counter to the parabolic data seen in Fig. 8.1 for the 60-s, 2-min and 3-min models. Where each duration uses an individual time in the duration, *W'* is a constant number, so a more constant relationship is expected. The slopes in Fig. 8.2 for this parameter of the CP model are relatively flat, showing no real addition to the physiologically expected parabolic shape, and thus limiting this parameter's potential utility, as in Chapter 7.

8.4.5 Limitations

This study uses publicly available power meter data. Thus, for a given duration a maximal effort is not assured. It is also does not assure the quality of the power data. However, with a focus on track cycling durations, and using data taken from track racing, road racing and this affects all the models. Equally, the use of publicly available data ensures larger datasets and potentially more generalizable conclusions. Further, while there is variability in the data, as noted, with larger participant numbers this effect can be average out over the cohort studied. This amelioration is reflected in the linear model result most directly, and in the high R^2 values showing a broad range of reasonably clustered data, indicating the variability across riders was not necessarily large.

8.4.6 Implications

The value of these models should be to guide a rider to understand their strengths and weaknesses relative the demands of competition. APR, CP, and *W'* all provide a given power or time a power can sustained. *W'* has been developed to include a recovery component called *W'*bal assessing the depletion and restoration of high intensity energy (ATP-phosphagen and oxygen independent glycolysis) [376]. These models are useful for reflection. However, questions remain, based on the data, on the quality of the models, and for *W'*, are seen in its flat, low-resolution response across durations in the results.

The 60-s, 120-s, 180-s power models allow not only a reminder of the importance of event specific power but can be used with a database of mean maximal power from two durations. Riders sitting above the line of best fit will be power strong, while riders below the line will be capacity strong. This outcome gives a strong indication of how to train towards a peak performance. Chapter 6 provides information for sprint cyclists and shows how the best performers were below the line, and over 3 x 4-week blocks they progressed up towards the line, and then when aiming to peak, lifting upwards over the line to maximize race winning power for their specific event.

Finally, there is a further coaching implication in considering the linear total least squares modelling of the power duration curve across all durations. Specifically, its ability to help coaches guide overall training to improve the entire power duration curve to improve overall athlete outcomes. This approach stands in stark contrast to currently accepted coaching methodologies focusing on a single power but are enabled by the modelling methods presented throughout this thesis and are easily implemented with readily available power meter data.

8.5 Summary

The data in this chapter suggest the linear and total least squares based model of the power duration curve offer better quality assessment of power than the anaerobic power reserve (APR) and both the 2-parameter critical power model (CP) and its *W'* parameter alone. It also has the added benefit of be able to guide a cyclist towards peak performance in competition through understanding where they are on the line of best fit for any pair of durations of interest, to train for either race winning power, or capacity, as well as to help guide overall training to improve the entire power duration curve, rather than currently accepted coaching methodologies focusing on a single power.

CHAPTER 9: Power-duration relationships for track endurance mass start event cyclists: Comparison to critical power and functional threshold power models

9.1 Introduction

The mass start events are a uniquely challenging sporting event where riders start in a bunch and must not only measure their performance against the distance and environmental conditions, but also against competition, where riders use tactics to perform to their best. Cyclists make use of bicycle based power meters, to measure in watts the power delivered in a race to assess their own performance and to understand the demands of the race. An understanding of the gap between what is required to win and what the rider can currently achieve assists in the planning of subsequent including how hard to train, and where in the season to sequence distinct types of training.

While it is intuitive to look at race data and use it to target training to the race, a strong feature of mass start track cycling events in particular, is the wide range of different events including Olympic events, such as the Omnium, which combines 4 races where a rider scores points to secure a result, and the 2 person points race team event, the Madison. These mass start events require a range of power durations depending on how the race develops. Critical Power (CP) has been proposed as one method to achieve the goal of assessing power across different durations, though the choice of these durations are arbitrary [190, 191, 305, 306]. Taking power for 2-5 maximal exercises tests of durations 2-12-mins in the severe exercise domain, between the lactate threshold and $\dot{V}02_{max}$, the asymptote is determined and considered to reflect a transition point between the heavy exercise and severe exercise domains [329]. The amount of work in kilojoules above this point is the finite high intensity exercise pool referred to as *W'* [306, 377].

There have been criticisms of applying the CP model to applied settings, because of the challenges of determining the measure with 2 parameter options referenced above, 3 parameter models [193], the use of a 3-min all out test [378], and more sophisticated models [101]. There are also questions on how one should exactly perform these tests, and the rationale for 2-5 tests between 2-12-mins [198, 249, 250]. The unclear nature of CP, and how it is determined, has meant high performance athletes still use laboratory tests, such as ramp tests to assess a lactate/ventilatory threshold [379], or a steeper ramp test to assess the $\dot{V}O2_{max}$ [380] to determine fitness levels and prescribe training levels.

Amateur and recreational cyclists employ more basic measures of fitness and simpler means of determining training zones, such as the functional threshold power (FTP), referred to as the quasi steady state power a rider can sustain for around 1-hour [381]. While several methods of estimating FTP based on power meter data are provided, the most rudimentary test is to perform a 5min all-out effort, then record a 20-min maximal effort and take 95% of this value [381]. It is still unclear if the effort to determine critical power and *W'*, or the expenditure of time and money in the laboratory for those tests, provides any performance benefit from the claimed benefits seen in return.

Ferguson et al. [315, 361] developed a simple method using total least squares models of performance, using comparisons of power for two durations, and across a range of power durations associated with the performance of interest show the strongest relationships. This study compares this method for three durations with a the 95% of 20-min power estimate, and the critical power asymptote and *W'* to examine the relationships.

The hypotheses evaluated in this chapter are:

- **A.** While there are strong relationships between critical power asymptote and *W'*, the stronger relationships will be observed with the total least squares linear model proposed in this thesis showing a stronger relationship to actual performance.
- **B.** Due to the complex nature track cycling bunch races, it is hypothesized a more complex model such as critical power will model performance better than one-off tests.

9.2 Methods

9.2.1 Study Design

Publicly available data from a group of national level cyclists was used. The publicly accessible Strava website data was acquired according to their Strava Privacy Policy (https://www.strava.com/legal), using the Sauce extension for web browsers (https://www.sauce.llc) to download file in *.tcx format. The WKO5 (TrainingPeaks, Boulder, CO) analysis software was used for power meter data to upload data files to determine power-duration data for each cyclist.

9.2.2 Participants

Table 9.1 summarizes the participant data for the study. A total of thirty-six datasets were found for endurance cyclists. From the Strava data, the age and weight of the rider were determined. Because of the public accessibility of data on the Strava website, the University of Canterbury Human Research Ethics Committee exempted this study from needing to seek ethics approval (2022/06/EX).

Table 9.1: Participant data presented as median and interquartile range [IQR].

	All	Male	Female
Participants	69	60	9
Data Sets	144	128	16
Age	26 [17 – 38]	27 [17 – 39]	19 [17 – 30]
Weight	70.0 [65.0 – 75.5]	72.0 [67.0 – 76.0]	57.0 [56.0 – 63.5]

9.2.3 Models Used

1. Linear relationship starting through the 0.0 power point [315].

60/120/240 second Watts = (a0·x)

Where *a0* is the constant coefficients found by identifying the best function for each case from the measured data, and *x = duration.*

2. Functional Threshold Power [382].

*FTP = 20-min mean maximal power * 0.95*

3. 2-Parameter Critical Power Model [329].

$P_{(t)} = \frac{W'}{t} + CP$

W' = work in kilojoules above the critical power, CP = Critical Power. For this study, 4 time durations of 2-min, 4-min, 8-min and 20-min were used to determine Critical Power and *W'*.

4. W' model [369].

$W' = A + B \times T_{lim}$

W' = limit of work (joules), A = a fixed energy reserve (J), B = critical power (W), and T_{lim} = time limit (s).

9.2.4 Analyses

All models were assessed using Matlab version 2023a (The MathWorks Natick MA). All models were evaluated using total least squares [311, 312], and by starting through the 0.0, all energetic pathways acting simultaneously was accounted for. Model quality was assessed using the total least squares correlation R^2. Slope measurement was used to determine the relationship between the two variables.

9.3 Results

Table 9.2 shows the R^2 slopes for all the four models for 5-s, 30-s, 60-s, 2-min, 3-min, 4-min, 5-min, 8-min. 12-min and 20-min. Fig. 9.1 shows the R^2 for all five models and all durations. Fig. 9.2 shows the slopes for all five models and all durations.

Table 9.2: R^2 and slope for all five models.

Time		30-s Power	3-min Power	8-min Power	FTP	CP	*W'*
5-s	R^2	0.94	0.95	0.96	0.96	0.96	1.00
	Slope	0.67	0.38	0.32	0.28	0.27	0.023
30-s	R^2	1.00	0.94	0.94	0.94	0.93	0.99
	Slope	1.00	0.56	0.47	0.41	0.41	0.034
60-s	R^2	0.96	0.94	0.93	0.93	0.92	0.99
	Slope	1.30	0.74	0.63	0.55	0.54	0.043
2-min	R^2	0.94	0.98	0.96	0.95	0.93	0.98
	Slope	1.62	0.93	0.78	0.68	0.67	0.052
3-min	R^2	0.94	1.00	0.97	0.96	0.94	0.98
	Slope	1.77	1.00	0.85	0.73	0.72	0.058
4-min	R^2	0.94	0.99	0.98	0.97	0.95	0.97
	Slope	1.86	1.05	0.89	0.77	0.76	0.060
5-min	R^2	0.94	0.98	0.99	0.98	0.95	0.97
	Slope	1.93	1.08	0.93	0.80	0.79	0.063
8-min	R^2	0.94	0.97	1.00	0.98	0.95	0.97
	Slope	2.10	1.18	1.00	0.87	0.86	0.069
12-min	R^2	0.94	0.97	0.99	0.99	0.97	0.96
	Slope	2.20	1.23	1.04	0.91	0.90	0.071
20-min	R^2	0.94	0.96	0.98	1.00	0.99	0.95
	Slope	2.31	1.30	1.09	0.95	0.94	0.072

9.4 Discussion

The intent of the study was to compare the linear model from Chapters 3,4,7, and 8 against FTP, CP, and *W'*, from CP. The main finding was a remarkable similarity between all of the models. *W'* displays a linear drop from 1-s reflecting how it estimates the depletion of high intensity energy during exercise above CP. Of interest, for a one off test, the FTP had a higher relationship with linear model durations than CP.

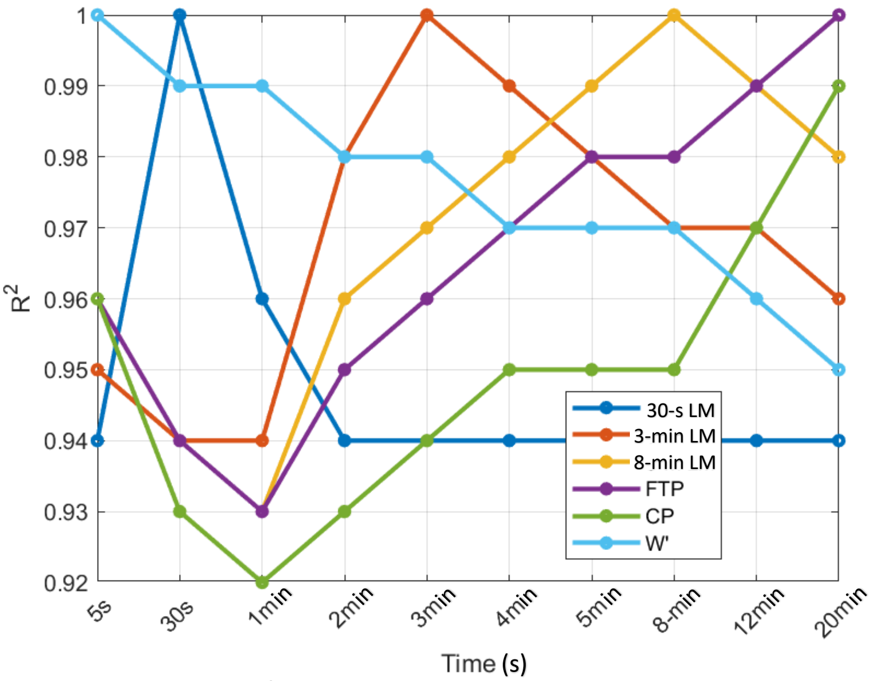


Fig. 9.1: R^2 for all 5 models over all the durations

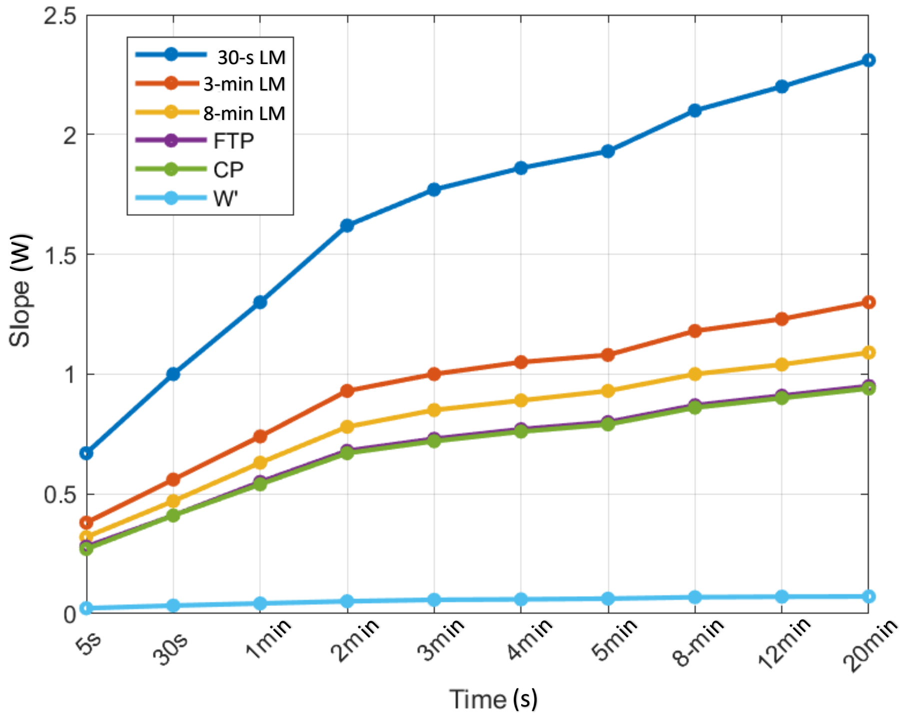


Fig. 9.2: Slopes for all 5 models over all durations

9.4.1 Total Least Squares Model for 30-s, 3-min and 8-min Power

Chapters 7 and 8 used power durations higher than the model power, for example for 15-s model time duration model 30-s and longer were used, where a parabolic relationship was observed. A similar parabolic relationship was observed for all three durations. This data shows the best predictor of 30-s, 3-min and 8-min is the power-duration evaluated itself. A bunch race, where a rider may need a good sprint to win (30-s power), ability to pursuit away near the end of a race (180-s power), and the ability to try and gain a lap on the field (8-min power), suggests the need for a model covering several durations to indicate strengths and weaknesses to determine tactics for a given event.

9.4.2 Functional Threshold Power (FTP)

Identical relationships were observed between all three durations of linear models and FTP. This result has implications for the athlete who needs to make decisions on whether they spend days completing multiple trials to determine CP and *W'*, or travel to a laboratory to perform tests measuring expired gases or take blood samples. More specifically, the time and economic costs of testing are high versus the simplicity of using field-based power meter data, and these results show the total least squares based linear model provides effectively identical outcome data for zero interruption or intrusion into training.

9.4.3 Critical Power (CP)

While the mathematics behind the critical power model has been constantly developed, taking it from a measure of fatigueless power for a long duration [191], towards a measure of the transition from the heavy exercise domain to the severe exercise domain [383]. The data showed both the linear model for all three durations, and even the simple FTP test, had a higher relationship. This result suggests if one was to try and model power in the severe intensity domain, a test of event duration or distance will be more specific, and thus CP may not provide meaningful coaching or athlete input.

9.4.4 W' parameter of CP

As seen in Chapters 6 and 7, the relationship for measures of power in the extreme and severe exercise domains remain high for *W'*. However, the relationship drops away as the durations shift from extreme to severe exercise domains, reflecting the utility of the *W'* model is best for the extreme domain only. One challenge to using *W'*, is it requires a full set of testing to obtain the number, which is only used in reflection. The slope depicted in Fig. 9.2 related to this parameter of the CP model exhibit a relatively gentle incline, which shows a lack of resolution across the domain, where small changes, due to rider variability in testing, would exceed this slope. This limitation constrains the practical effectiveness of this parameter, aligning with the observations made in Chapters 7 and 8.

9.4.6 Observations between the models

What is seen from the data in this chapter comparing models is similarity between the different models, even if resolution is higher or lower across domains. The data shows performance tests of a specific duration in this study, and Chapter 3-9, all support the use of the linear model proposed in this thesis due to its simplicity and the fact it is readily obtained from field data versus intensive testing.

Overall, this chapter hypothesized the utility of CP testing may be useful to the complex nature of any bunch race on the track. Its ability to cover multiple durations for bunch racing was thought to imply the ability to provide a more useful, single value to guide training for these events. However, the data and analysis presented did not support this contention.

9.4.7 Limitations

This study uses publicly available data, and therefore not tests of each specific duration used. However, for the purposes of this study, all calculations are based on similar data, and the data is valid. These power durations can be biased where a rider may focus on set durations, such as a 2000-m pursuit rider on 2:30 min power, 3000-m on 3:30min power and 4000-m pursuit rider on 4:30-min power, where the specialty power will be higher relative to other durations.

9.4.8 Implications

The data here show little advantage for critical power testing requiring several trials performed maximally. In particular, several maximal trials do not compare well to a one off test of 20-min giving similar results when using the linear model proposed. Further, the linear model does not require costly equipment to perform laboratory tests or take time away from rider training and recovery.

The data thus confirm previous associations of the power duration curve, and the proposed linear model of sprint and track endurance cycling performance (Chapters 3,4,5,7, and 8). The linear model can be used to determine if a rider has good capacity, the ability to hold a given power for a duration, or good power, the ability to deliver power. Chapter 6 highlights how a sprint cyclist is best to start with good capacity and over 3 x 4-week blocks they progress upwards towards the line and in the final block they train above the line to develop race winning power.

9.5 Summary

The study shows similar relationships between a model of specific durations, a basic FTP test, and the more complex CP model. The main outcome is these tests perform no better than the linear total least squares model proposed and presented throughout the thesis. In addition, the time and economic costs of specialist testing are high versus the simplicity of using field-based power meter data, and these results show the total least squares based linear model provides effectively identical outcome data for zero interruption or intrusion into training.

Chapter 10: Conclusions

The primary thesis of this research was developing a better understanding of track cycling performance, relevant to the actual supply and demand encountered in racing. An investigation of the current research showed several predominant models or tests used in track sprint cycling (Wingate test, Anaerobic Power Reserve etc.), track endurance cycling ($\dot{V}O2_{max}$, lactate or ventilatory threshold, critical power etc.). These tests can prove impractical, take time, be invasive, interrupt training progress, and invoke expense. This thesis compares these tests/models with field-based data. The overall hypothesis was field based tests offer greater validity, as well as practicality, allowing the track cyclist to spend more time focusing on the aspects of fitness they need to train as part of the overall performance goal.

In particular, field-based tests do not interrupt training and offer no specific added expense as power meters are common in elite cycling. Further, field-based power metrics may better reflect the entire power duration curve, all elements of which are seen to be necessary in this thesis. Finally, power meters offer "real-time" feedback as they can be used every training session, providing coaches with every day, or "real-time", feedback on how athletes are progressing. Such repeated and regular measures offer more chances to intervene and optimise training to achieve best performance, when compared to specific, often maximal tests.

Chapter Three evaluated four different models using both track cycling sprint and track cycling endurance data. Firstly, the evaluation showed a linear model was better than exponential, parabolic and power equation models. Secondly, applying the applying the linear model to comparison of 15-s and 30-s powers (two common durations of sprint cycling) a strong relationship between these powers and the power durations of 2-min, 8-min and 20-min remained high where it would be expected to see a sharp drop off if peak power was the key metric of sprint cycling performance.

Chapter Four used the best model from Chapter Three to compare 15 and 30 second power against durations from 1-s to 20-min. Having confirmed the sprint cyclists were sprint cyclists by comparing their power against a group of endurance athletes, strong relationships were observed for all durations, and a parabolic relationship across these durations. This result shows competition durations are the most important determinant of competition performance and, not only is 1-s power important but power durations out to 20-min have a positive impact on sprint performance.

Chapter Five applied the model to evaluate differences between male and female track sprint cyclists. The data showed similar slopes between 15 and 30 second power for watts per kilogram. However, the R^2 showed women had a higher variability around these lines, suggesting more subject-specific responses than for men. This outcome suggests women could benefit more than men from the "real-time" feedback provided using field-based power metrics and models to guide training. The outcome also highlights the importance for women, to assess their performance in relation to race winning power over capacity. This outcome is further highlighted in Chapter Six.

Chapter Six describes the progression of 25 sprint cyclists towards a performance in a key competition. 12 weeks of training was broken into three 12-week blocks. The data shows the best performing cyclists are those who started below the line of best fit for 30-s and 2-min, and trained up towards the line, and in the final block they trained up above the line. In terms of periodization, this data shows a *long too short* approach starting with building capacity and progressing towards developing race winning power was the optimal approach.

Chapter Seven compares the linear model against the anaerobic power reserve and both aspects of the critical power model (asymptote and *W'*) for sprint cycling performance. The linear model had the best relationship with 15-s and 30-s power, where both anaerobic power reserve and both aspects of critical power are biased by the construction methodology.

Chapter Eight applies the linear model against anaerobic power reserve and both aspects of critical power for pursuit cycling. For the durations of 60-s, 2-min and 3-min it was found, the linear model was the best fit of the data. As found in Chapter 7, potentially the methods of determining APR and CP bias the measures depending on the inputs.

Chapter Nine applied the linear model to the track cycling mass start events. Here it is expected critical power model to would offer a better model of bunch racing performance, however the linear model prevailed.

The general conclusions of this thesis are based on the key hypothesis tested overall throughout the thesis, specifically:

There is a parabolic relationship to event specific power in comparison to general power, disproving the notion of a linear relationship where peak power acts as a governor to performance, and thus its primary determinant. Further, this power duration curve can be used to guide athlete-specific training.

A key finding in Chapters 3, 4, 5, and 7, was the parabolic relationship for both sprint competition durations, and in Chapter 8 and 9, track endurance durations. This outcome is novel in the field. Unsurprising, it also shows the best predictor of performance for both sprint and pursuit duration power for those specific durations. The implication for performance is the key focus should be on durations relevant to performance, rather than peak power. Equally, Chapters 3-9 in combination show how training all durations can optimise performance in terms of repeated sprints or time trials in each major event, which is highlighted further in the results of Chapter 6, which uses these power duration curves to assess training.

A first main outcome overall of this thesis is thus disproving the notion of peak 1-s power being the primary driver of sprint cycling performance. Two commonly used models for the power-duration curve, the anaerobic power reserve and critical power (asymptote and *W'*), both had strong correlations. However, they were not as strong as the linear model. The shape of the curves was not parabolic, which suggested there was bias in the model reflecting issues in the calculation of both metrics.

The parabolic relationship for these durations invalidates the notion of peak power metrics governing performance in a linear fashion. This notion was also disproved when strong correlations for sprint competition power (15 and 30 second) were seen out to 20-min of durations. While competition specific performance is a key to racing, the strong correlations for both peak power and capacity suggest a cyclist needs to perform a wide variety of durations to achieve their best results.

A second main outcome of this thesis is there are sex differences in performance between male and female sprint cyclists. With finding of women having greater variability in sprint cycling power, the implication is it is even more important to use the linear model to specifically train towards race winning power, or sprint capacity.

This total least squares linear model, also applies to track endurance cycling, disproving the notion of either peak power or power at the $\dot{V}O2_{max}$ drives performance in these events. The same parabolic relationship using the linear model for the three pursuit power durations of 60-s, 2-min and 3-min was observed, showing again, the most important performance metric is performance itself.

Finally, this thesis provides valuable information to assist a coach in prescribing exercise towards peaking for a key sprint cycling event. Chapter 6, culminating the presentation of the linear total least squares power duration curve model shows how the best improvements come from riders training towards the line of best fit, regardless of where they start relative to this line. This result endorses the long to short approach for training sprinters, while the linear model presented provides a field based, easily obtained means of monitoring, guiding, and optimizing rider performance in the framework.

Chapter 11: Future work

11.1 Modelling Sprint Durations

Future work on modelling sprint durations of 15-30 seconds and out to the 60-70 seconds of the Kilometer time trial, is obtaining more data from high performance cyclists. Lievens et al. [384] showed different muscle fiber typology (MFT) between BMX riders, sprint cyclists, Keirin cyclists, pursuit cyclists and bunch race cyclists, progressively showing a faster MFT as event duration decreased. The data in this thesis used National level athletes, with some sprinters crossing over to selected endurance events. High performance data would clarify differences between the two groups.

None of the current sprint tests make any estimation of recoverability. All sprint cycling events at World Championships require repeated performance from qualifying to the medal rounds. The ability to recover fast, especially at the Olympics where often television schedules dictate session times, is a priority for sprinters. In another study by Lievens et al. [203], it was observed how participants with a fast twitch MFT had substantially longer recovery from a maximal exercise test, than those with slow twitch MFT. Considering Chapters 3,4,5, and 6, it is clear in National level sprint cyclists performing maximal efforts enhances sprint performance. Testing of recoverability between sprints is clearly beneficial, especially in sprint competitions which may have short gaps between rounds. Recent work from Dale et al. [385] and Desgorces et al. [57] have started to shed light on recoverability in sprint cycling.

11.2 Testing Pursuit Durations

Going back to the observations of the German Men's Team Pursuit at the 2000 Sydney Olympics [65], where the team won the gold medal in a new world record, performing little specific team pursuit practice and an large amount of riding well below race pace, a clear area of opportunity is modelling the importance of what is referred to as *base fitness* to determine the impact of non-specific training is on performance.

Again, with repeated efforts being required to medal in the Olympic team pursuit (3 rounds), or the World Championship individual pursuit (2 rounds), the importance of recoverability is relatively untested. The *W'*bal model has been applied to the team pursuit event for a given ride [386], but not for recoverability between rounds. Observations from competition where riders fail to perform in subsequent rounds need to be evaluated.

11.3 Testing Bunch Race Durations

Prior research of the Omnium events has not been updated to reflect the new rules brought in after the Rio de Janeiro Olympics of 2016 [387-389]. Stanley, Wilson and Wainwright [390] cover the positioning of the points race final event of the Omnium. Again, the *W'* component of critical power is a candidate for this and could be a potential start to a model the complexity and opportunity in mass start events. However first, more work needs to take place to connect critical power, or any power meter based data model, to the underlying physiology [250].

Lactate or gas analysis are currently used in the laboratory but lack the practicality to measure in the field. Near Infrared Spectroscopy [391], or heart rate variability [392]. Both metrics can be used to estimate performance in the field alongside power to develop better mathematical models of cycling performance.

11.4 Cycling Performance Models in General

As seen in all chapters of this thesis, current performance models based on field-based measures, have proved inadequate to model performance compared to the linear model. While, for a given duration the linear model is best, there are still challenges with just using a one-off measure for performance in general.

Firstly, within a ride over any given duration or distance, the one-off power is the best predictor of performance, however the one off test gives the coach no indication of how the power is achieved. Whether a rider is power strong or capacity strong. Chapter six does describe how strengths and weaknesses can be assessed for sprint cycling, contingent on having a good base of, in the example, of data on sprint cyclists to obtain a good line of best fit to estimate if a cyclist is peak power strong (above the line), or capacity strong (below). Without a good base of data individual strengths and weaknesses cannot be assessed. Secondly, for races with variability within a race (most bunch races, in particular points races), or between races (a sprint series or the Omnium), the linear model can be used to assess several difference measures, however as shown, current models are inadequate.

11.5 Summary

Better models are needed: to determine areas of strength to be maintained, and areas of weakness (relative to the key events) to be developed. Then when peaking for events to focus on the strengths and maximize them and use this information to make the best tactical decisions based on racing to those strengths!

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