Optimizing Cycling Performance: Comprehensive Analysis Using OMPD, Weather Influence, and Team Dynamics

Jiahang Zhang *

School of mathematics NUAA, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 211106

* Corresponding Author Email: 082010125@nuaa.edu.cn

Abstract. Competitive cycling requires strategic power management, influenced by individual abilities, environmental conditions, and team coordination, to achieve optimal performance in diverse racing scenarios. This study introduces an enhanced simulation model for cycling performance, which replaces the traditional CP model with the OMPD model and incorporates elements like fatigue, weather, and road information for a more comprehensive analysis. The model is applied to various tracks to analyze individual cyclists' power output, fatigue, and abilities. It reveals significant power differences between male and female cyclists. The study also extends the model to team dynamics, examining how a six-person team, functioning as a single unit, can achieve higher overall power and efficiency compared to individual performances. Furthermore, the model includes a weather system and assesses the minimal impact of weather conditions on cyclists. Through repeated simulations, the robustness of the model and its effectiveness in predicting race outcomes are demonstrated, providing valuable insights for coaches and cyclists in strategizing for competitive racing.

Keywords: OMPD, Simulation, Power-time curve.

1. Introduction

In the realm of competitive cycling, success hinges on meticulously balancing various factors: the precise management of a cyclist's power output, the impact of varying environmental conditions such as weather and terrain, and the intricate dynamics of team strategy [1, 2]. Each of these elements plays a pivotal role in shaping race outcomes, demanding a nuanced understanding and integration of individual physical capabilities, tactical adaptability to changing conditions, and the collective efficiency of team collaboration [3, 4]. This complex interplay defines the competitive landscape, where precise analysis and strategic planning become essential for triumphing in challenging and diverse racing environments [5].

In our research, we embarked on a comprehensive exploration of cycling performance, employing a methodical approach that encompassed both individual and team dynamics in competitive cycling. Our journey began with the adoption and enhancement of the Optimal Mixed Power Distribution (OMPD) model, a significant shift from the traditional models used in cycling analytics. We meticulously gathered and analyzed data from individual cyclists, taking into account various factors such as power output, fatigue, and personal abilities. This analysis was not only focused on quantifying these aspects but also on understanding their implications in the context of long-distance cycling. Progressing further, we expanded our focus to include team dynamics, exploring how groups of cyclists operate as a cohesive unit and how their collective performance compares to individual efforts. Additionally, we integrated environmental factors such as weather into our analysis, examining their influence on performance. The culmination of our work was a series of simulations, each aimed at testing the robustness of our model and its applicability in real-world racing scenarios, thereby offering valuable insights for strategy formulation in competitive cycling.

2. Establish Rider Power Curve Model

According to the requirements of the race, the driver needs to run the given distance in the shortest time, which requires the driver to generate a large amount of power output in different time periods.

Their ability to do so can be summarized as a power-time (PD) curve. The PD curve can be estimated from the driver's maximum average power (MMP) curve, which is a function of several biological and technical factors, hindering direct interpretation. So we use the two-parameter power (2-CP) model [6].

$$P(t) = \frac{W'}{t} + CP \tag{1}$$

Where P represents the maximum average power within the duration t, CP represents the critical power, and W' is the amount of mechanical work that can be achieved when CP is exceeded.

A few parameters were used to summarize MMP data, while 2-CP model was not suitable for predicting long duration motion. We extended it to global power-duration model (OMPD) and found that it had better approximation to MMP data than 2-CP and 3-CP models. The OMPD model aims to solve the shortcoming of the 2-CP model's limited predictive power outside the severe intensity domain [7]. The OMPD model integrates two models, one for long time and one for short time. OMPD model can be expressed as Eq2:

$$P(t) = \frac{W'}{t}(1 - e^{-t\frac{P_{\max} - CP}{W'}}) + CP; t \le TCP_{\max} \tag{2}$$

$$P(t) = \frac{W'}{t}(1 - e^{-t\frac{P_{\max} - CP}{W'}}) + CP - A \cdot Ln(\frac{t}{TCP_{\max}}); t > TCP_{\max} \tag{3}$$

TCPmax represents the critical value of extending CP model duration, after which the muscle could not withstand excessive lactic acid, resulting in further power decline. Pmax represents the maximum power that the driver can achieve, A is the fixed constant of output power decreasing with time, and Ln is the natural logarithm of e (2. 718).

Through relevant literature , we quantified the abilities of various types of athletes on a scale of ten points. As shown in Table 1.

Table 1. Rider's ability

ability \ type	C	R	S	T	P
sprint	6	8	10	6	8
climbing	10	8	7	9	9
restore	9	8	8	8	7
Weight(kg)/Height (cm)	59/167	66/181	76/181. 5	65/180	60/175

We choose T-rider and R-rider for power curve analysis. Based on the above data analysis and the comparison of various physical data of ordinary adults, we can estimate the A value and W 'value of each type of driver in OMPD model , then we assign values to the parameters of T-rider and R-rider assignment. The specific parameters are detailed in Table 2.

Table 2. Rider's various indicators

Rider type	TCPmax	Pmax	CP	A	W '
T	1480	1280	300	20	5700
R	1600	1440	300	40	5400

In road cycling, the weight of different types of athletes often varies greatly. After understanding the physical conditions of some athletes, we obtained some rough estimates of the weight of different types of athletes and then calculated various parameters in the OMPD model.

After obtaining the required parameters, we define the athlete's power curve. It is assumed that the power curve corresponds to the function of the maximum power output of athletes and the competition duration. Taking R and T male and female athletes as examples, the following four power curves can be illustrated in Figure 1.

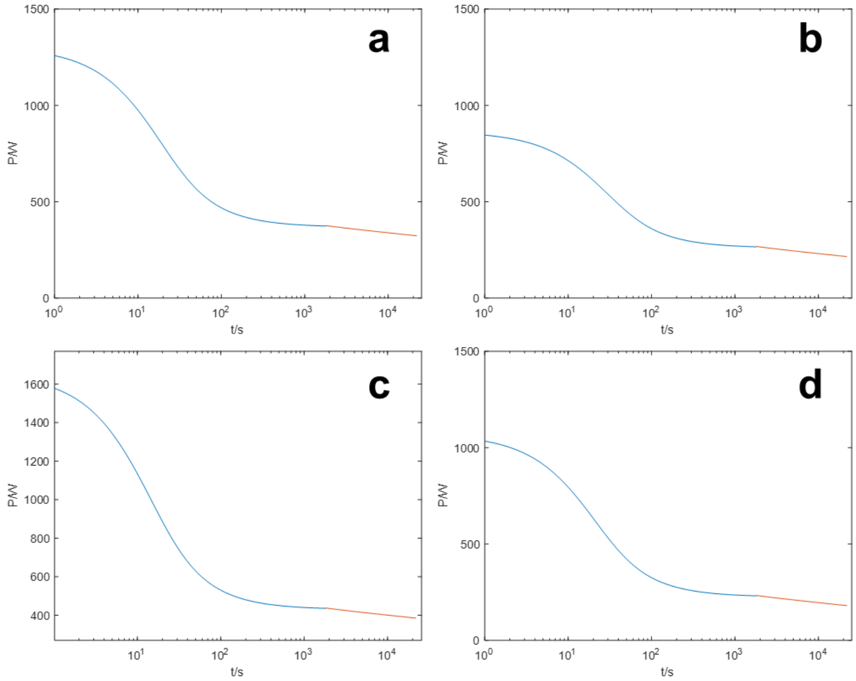

Figure 1. Power-time diagram of the rider.

a: male T-rider. b: female T-driver. c: male R-rider. d: female R-rider.

3. Implementation of a Fatigue Management Mechanism

Herein, we have established a fatigue system in our model to account for the natural progression of tiredness in drivers and their ability to exceed the power curve. This system incorporates parameters for fatigue value and a fatigue reduction rate of 1 point, effectively depicting the acceleration and deceleration phases of the driver's performance [8].

In developing this model, we base our approach on four key assumptions: (1) The model excludes the impact of accidents. (2) Environmental factors that could contribute to driver fatigue are not considered. (3) We use an average power value of 378W, which is the point at which fatigue begins for a typical driver, as our standard benchmark. (4) The model assumes that drivers overcome fatigue in the final 200 meters of the race.

Additionally, to accurately simulate the effects of gravity, friction resistance, air resistance, and the differences in speed on flat and uphill terrains, these factors are integrated into our velocity formula.

$$gk \times \sin(\frac{\pi}{2} \times r) \tag{4}$$

$$hk \times vt^2 \tag{5}$$

Where r is slope, *gk* is gravity influence coefficient, *hk* is the coefficient before the V^2 term of air resistance formula.

$$F = \frac{1}{2} C \rho S V^2 \tag{6}$$

Which is related to altitude, and fk friction resistance is introduced.

To evaluate the real-world effects of driver fatigue, we simplified and constructed the time trial models of 2021 Tokyo Olympic Time trial and 2021UCI World Cup time trial in Flanders, Belgium. For the self-made track model, we set up four turns and four hills, as shown in figure 2.

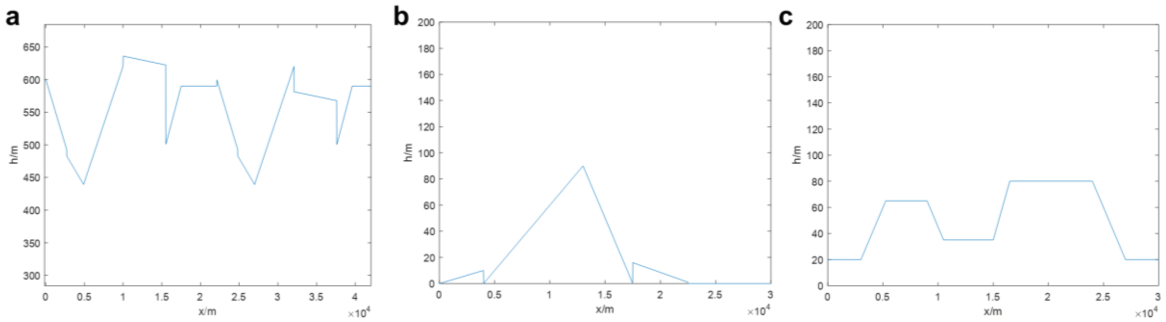

Figure 2. Schematic diagram of the race belt model.

a: 2021 Tokyo Olympic Time trial. b: 2021UCI World Cup time trial in Flanders, Belgium. c: self-made track.

In addition, the simulation model and fatigue system are incorporated into the three track models. The following are the section diagrams of the three tracks. Then we applied the simulation model to three circuits respectively, and obtained the fatigue degree-time curve and the power-time curve of the simulation.

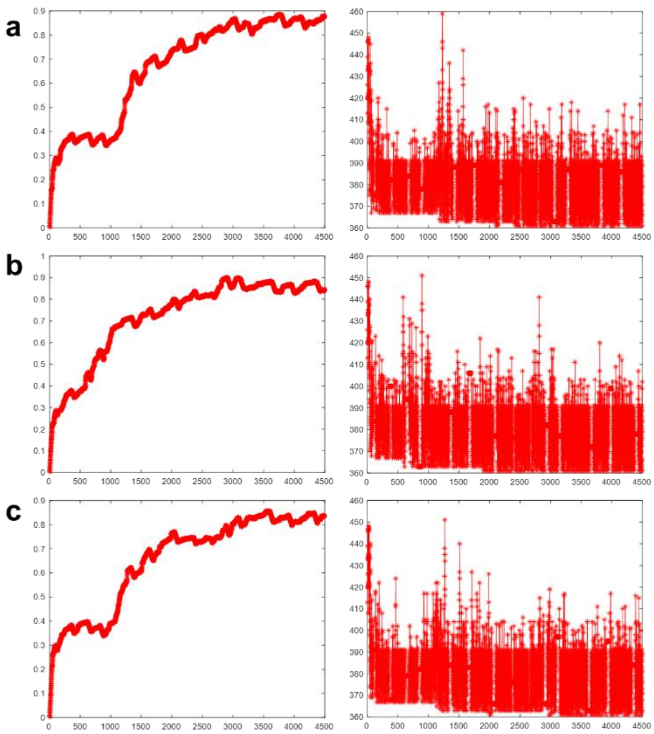

Figure 3. Diagram of the results of the track simulation.

a: 2021 Tokyo Olympic Time trial. b: 2021UCI World Cup time trial in Flanders, Belgium. c: self-made track.

4. Simulating Driver Response to Weather and Fatigue Variables

Investigating the interplay between weather elements and driver dynamics, we enhanced our simulation model by integrating wind direction and velocity, building upon our previous analyses. This addition allows for a nuanced examination of how weather conditions affect vehicular movement.

We operate under the premise that wind patterns are inherently unpredictable, with their primary influence manifesting as variations in vehicular speed—providing acceleration when aiding movement and deceleration when opposing it. The results of the model are depicted in Figure 4.

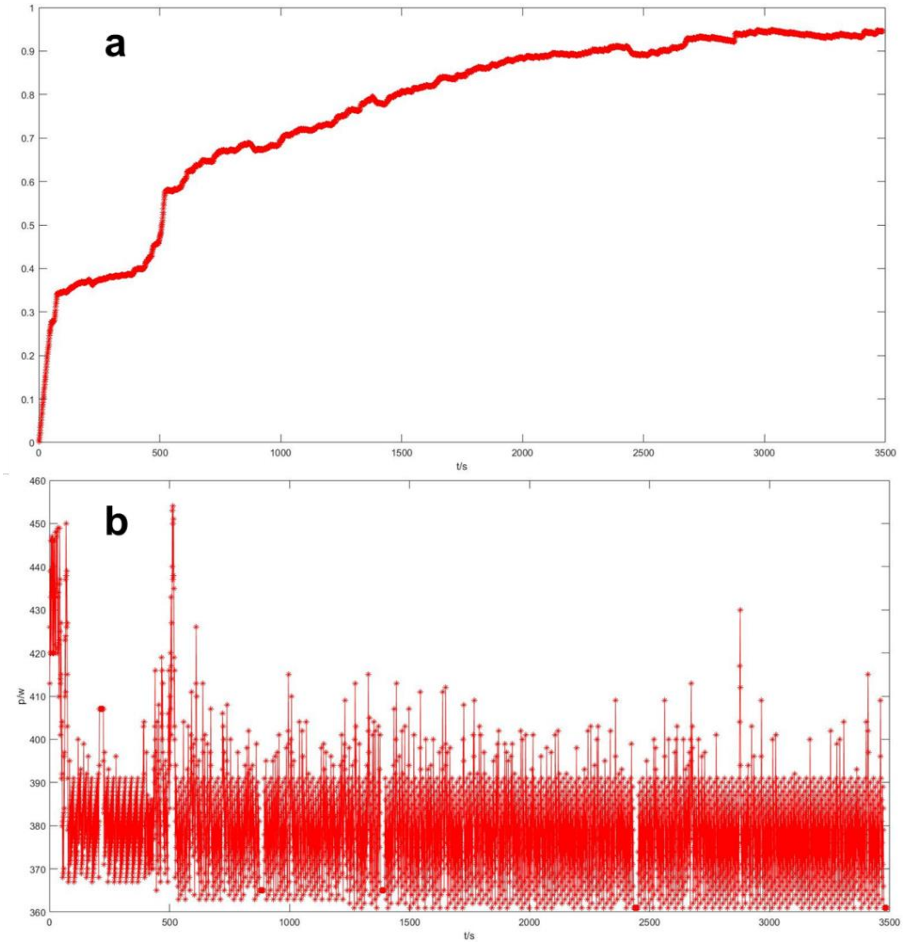

Figure 4. Diagram of taking into account the weather factor

a: fatigue degree-time curve. b: power-time curve

Further delving into the model's responsiveness, we conducted a sensitivity analysis by incorporating the weather system into the proprietary road model developed by T-man. Comparative assessment with previous iterations, specifically Figure 3, indicates a marginal impact of wind conditions on driver trajectories.

Extending our analysis to the sensitivity of driver deviation in response to power distribution, we accounted for random variables within the program—specifically, the probabilistic changes in speed during periods of fatigue. By simulating T-rider's data multiple times, we generated fatigue degree-time and power-time diagrams for the user-defined track. The observed variances, depicted in Figure 5, remained within anticipated bounds, underscoring the robustness of our simulation model in reflecting realistic driver responses to fluctuating weather patterns and fatigue-induced performance shifts [9].

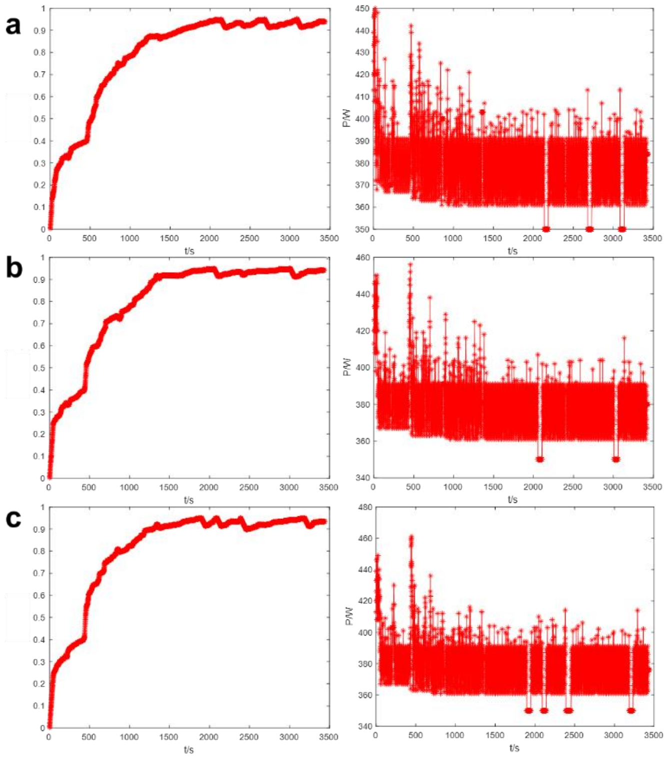

Figure 5. Results of multiple runs.

a: 2021 Tokyo Olympic Time trial. b: 2021UCI World Cup time trial in Flanders, Belgium. c: self-made track.

At the same time, we recorded the time taken by T-rider to complete the race and made a chart. As shown in figure 6.

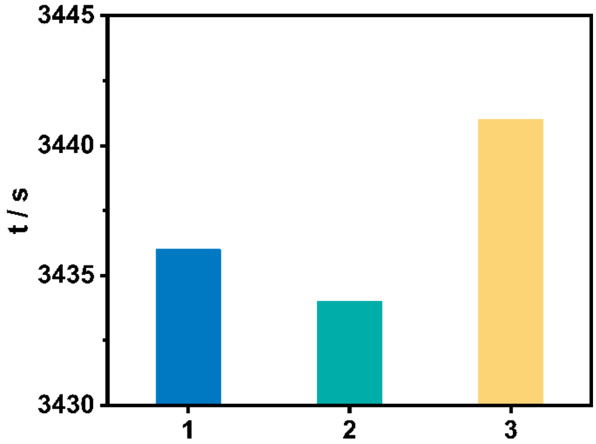

Figure 6. Run the model results multiple times.

To sum up, running the model repeatedly and comparing the results obtained each time, it is found that the discrete degree of the results is very small, and the model has good stability.

5. Team Competition Model

Herein, we have extended the simulation model, which was initially developed for individual cycling competition, to now encompass a team dynamic, specifically focusing on a six-person cycling team. Central to this model is the strategy of selecting a team leader who will be in the optimal condition for the upcoming segment of the race. This optimal condition is characterized by achieving the highest possible power output while keeping fatigue accumulation to a minimum [10].

We based our approach on the premise that the six team members will cross the finish line at approximately the same time, maintaining a relatively uniform distance and speed throughout the race. This assumption is critical in simulating realistic team dynamics in competitive cycling.

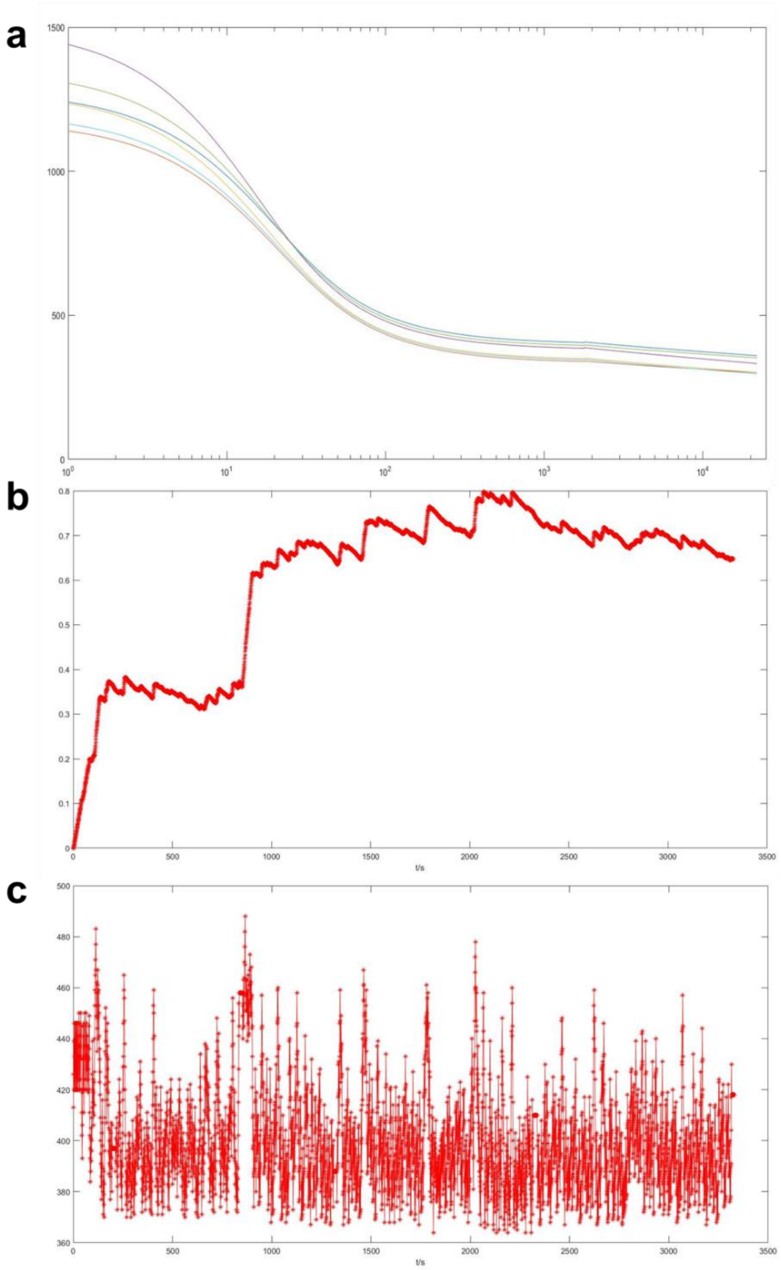

Figure 7. Teams OMPD and power-time simulation diagram.

To construct this team model, we drew upon the range of attribute parameters for four types of players (C, R, P, and S) defined in our initial analysis. From these, we formulated the attributes for six team members, selecting one C-type and one P-type player, complemented by two each from R and S types. For these cyclists, we generated their Optimal Mixed Power Distribution (OMPD), fatigue degree-time diagrams, and power-time simulation diagrams [11].

Our graphical analysis, as illustrated in Figure 7, reveals significant insights into team performance versus individual performance. The data demonstrates that the collective power output of a team is consistently higher than that of individuals on the same track. Moreover, the overall fatigue level experienced by the team is lower, and the time taken to complete the course is shorter. These findings highlight the enhanced efficiency and effectiveness of a well-coordinated team in competitive cycling scenarios.

6. Conclusions

In this study, we have significantly enhanced the analytical framework for competitive cycling by implementing the Optimal Mixed Power Distribution (OMPD) model. This approach has allowed us to delve deeper into the intricacies of individual performance, highlighting notable differences in power output among cyclists and underscoring the importance of tailored training approaches. Our extension of the model to team dynamics emphasizes the superior performance achievable through coordinated team effort, surpassing the capabilities of individual cyclists.

The minimal impact of environmental factors like weather, as revealed by our model, shifts the focus more towards intrinsic aspects such as skill and strategy. The robustness and reliability of our simulations underscore the model's effectiveness in real-world applications, providing valuable insights for coaches and cyclists alike. This research bridges the gap between theoretical modeling and practical application in competitive cycling, advocating for a holistic approach that balances individual talent, team synergy, and environmental considerations for optimal racing strategies and outcomes.

References

[1] Zhu Zhenghua. Rational use of bending technique in bicycle racing[J]. Talent, 2020(26): 208.

[2] Guo Ziyuan. Study on the change rule of function in mountain biking athletes during pre-competition training period: 2014 China Sport Physiology and Biochemistry Conference[C]. Guiyang, Guizhou, China, 2014.

[3] YANG Lin, YANG Yan, ZHANG Na, et al. Design of cycling race system based on cycling IM[J]. Computer and Digital Engineering, 2018,46(10): 2004-2010.

[4] Lu JH. Discussion and research on physical training of cyclists[J]. Modern Vocational Education, 2021(03): 178-179.

[5] CHENG Jianchuan, KONG Fanxing, LI Fang. Design and Optimization of Track Cycling Track[M]. 1. 1. Nanjing Southeast University Press: 119.

[6] XU Y, DAI Y, ZHANG H. Strategy Arrangement of Road Cycling Individual Time Trial Based on Topology Optimization Algorithm: Proceedings of the 6th International Conference on Medical and Health Informatics[C], Virtual Event, Japan: Association for Computing Machinery, 2022.

[7] WANG Zeyang, ZHAO Haobo, WANG Yifei. An all-terrain power distribution approach for bicycles based on OmPD model[J]. Heilongjiang Science, 2022,13(24): 66-69.

[8] Cui Xiaozhu, Li Dan. Analysis of oxygen uptake power model of different starting modes in track cycling 4000m pursuit race[J]. Sports Research, 2023,34(05): 77-80.

[9] PUCHOWICZ M J, BAKER J, CLARKE D C. Development and field validation of an omni-domain power-duration model[J]. Journal of Sports Sciences, 2020,38(7): 801-813.

[10] HUANG Wei, JU Jie. Research on the training methods of speed and speed endurance of excellent male sprinters in China--Taking Chen Wenzhong as an example[J]. Sports, 2022(15): 38-40.

[11] LEO P, SPRAGG J, PODLOGAR T, et al. Power profiling and the power-duration relationship in cycling: a narrative review[J]. European Journal of Applied Physiology, 2022,122(2): 301-316.