

Abstract

On the marginal gains of computed optimal pacing strategies

Ramona Burger, Alexander Artiga Gonzalez, Dietmar Saupe

Department of Computer and Information Science, University of Konstanz, Germany

* Correspondence: Ramona Burger. ramona.burger@uni-konstanz.de

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1. Purpose

In road cycling, the way an athlete distributes the available energy resources over the course of an activity is known as the pacing strategy. The right pacing strategy can be the crucial factor to win a race. There have been numerous studies to investigate pacing strategies. They either tried to find an optimal strategy using trial and error approaches (Swain (1997), Atkinson et al. (2007)) or mathematical approaches that optimize the power distribution (Gordon (2005), Dahmen et al. (2012)). Another source of pacing strategies are online platforms which offer the possibility to compute, download and use optimal solutions for pacing on the road. The aim of this study was to investigate to what extent optimal pacing strategies would be able to reduce the total riding time of cyclists at different personal performance levels. In the following, we compare optimal, computed strategies from the Powerbike project (Wolf (2019)) and from the online platforms BestBikeSplit and Strava with data from 12,202 maximum effort rides from Norton Summit (Adelaide, Australia), which is a popular 5.54 km long uphill road segment with a climb of 270.3 m (Saupe et al. 2019).

2. Methods

The pacing strategies were obtained for goal times of 11, 12, ..., 23, 24 minutes, corresponding to finish times achieved by best efforts of hobby riders up to professional athletes on the Tour Down Under. We compared the empirical and computed strategies for fixed average speed and average power. To estimate power for the

collected data, we used the physical model introduced by Martin et al. (1998). For this purpose, we configured a virtual standard rider, as described by Dahmen et al. (2011). Finally, we computed the average power and the average speed for each recorded ride.

3. Results

Figure 1 shows the optimal pacing strategies from Strava, Powerbike, and BestBikeSplit for a finish time of 12 minutes. Despite having the same finish time and nearly the same average power, the power distribution differs. The distribution of the Powerbike and BestBikeSplit strategies is rather similar with an average correlation 0.88 overall goal times. Strava follows a different approach with higher maximum power, up to more than 600 W for several hundred meters. Also, the average correlations of the 20 empirical rides which were closest to each goal time with the computed strategies are higher for BestBikeSplit (0.70) and Powerbike (0.71) than for Strava (0.49).

Figure 2 shows the differences in average power between the power corresponding to the empirical data and the computed strategy with the lowest average power corresponding to the average speed of the ride. In Figure 2, this computed strategy with minimal power requirement is given as the baseline at zero offset. Up to an average speed of 26.27 km/h the Powerbike strategy has the lowest power demand. For all higher average speeds, the BestBikeSplit strategy has the lowest power demand. The average differences in power between the three computed strategies are small,



approximately 0.36 W. We divided the riders into two groups: riders with an average speed less or equal to 29 km/h (99.78%) and riders with an average speed greater than 29 km/h. 71% of the riders of the first group yielded a higher average power ($0.70 \text{ W} \pm 0.72 \text{ W}$) than the optimal strategies. The remaining 29% yielded an average power below the baseline ($-0.27 \text{ W} \pm 0.27 \text{ W}$). The power of the fastest riders only deviated by $0.52 \text{ W} \pm 0.93 \text{ W}$ from the computed strategy with the lowest power demand.

4. Conclusion

We showed that the majority of the 12,202 riders of our empirical dataset could have slightly benefited from adapting to a computed pacing strategy on the 5.54 km hill climbing segment. Therefore, optimal pacing strategies may well serve as one of the components integrated into the concept of marginal gains that became popular in road cycling over the last years.

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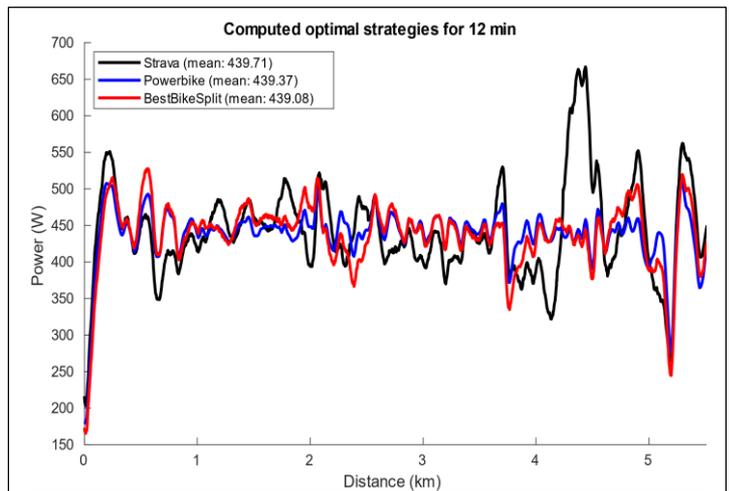


Figure 1. Computed optimal strategies from Strava, PowerBibe and BestBikeSplit for a goal time of 12 minutes.

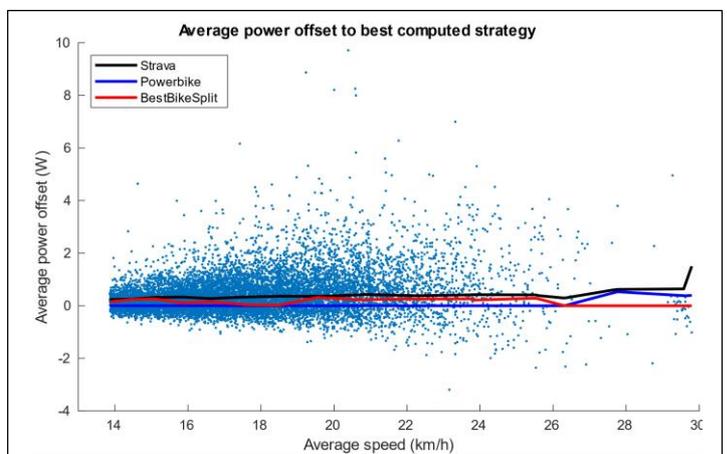


Figure 2. Scatter plot of the differences in average power to the computed strategy with the lowest average power of the empirical rides.