Problem Chosen: A

2025
MCM
Summary Sheet

Team Members
Dylan Jacobs,
Paolo Bosques-Paulet,
Joost Almekinders

Optimizing a Cyclist's Power Output Using a Genetic Algorithm

Summary

Professional road cycling is a highly competitive and demanding sport that combines strategy and endurance. Riders must employ strategies that optimally utilize their individual strengths for each specific type of race. To determine the optimal strategy for different types of cyclists during an individual time trial race, we developed a model that identifies the optimal pacing strategy riders should follow. The model is divided into four parts:

Model 1: Power Profile Model. To characterize the power profiles of two types of riders, we employ an ODE in conjunction with real-world cyclist data to fit the model. The approach allows us to estimate the power curves for a time trial specialist and puncheur.

Model 2: ODE Model and Physics We use the physical principles of motion to compute the resistance forces on a rider. Using the rider's output power, this model computes a rider's acceleration and velocity along the course for a given rider profile (e.g. time-trial specialist or puncheur).

Model 3: Skiba Model. To determine how much a cyclist's power output exceeds their critical power level impacts their overall energy capacity, we employ the Skiba model to regulate the cyclist's power output during the race.

Model 4: Genetic Algorithm Power Output Optimizer Model. We apply a genetic algorithm that varies parameters controlling cyclist power output at each time step along the race course, evaluating and optimizing power output performance by simulating race completion times.

Empirical Analysis. In addition to simulating finishing times for optimized cyclists, we also analyze the sensitivity of our model to changes in weather and deviations in rider output power from the optimal target power distribution.

Model Extension. We consider taking into account reduced air resistance for the riders further behind in the pack. We plan to designate a rider to take the brunt of the air resistance for a certain period of time, then have a different rider take that position, allowing the rest of the team to conserve energy while the 4th rider conserves energy in preparation for a final sprint.

Keywords: Power Curve, Genetic Algorithm, Skiba Energy Store Model, Critical Power.

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1 Introduction

1.1 Background

Figure 1: Mathieu Van der Poel at the finish line of a time trial race [2]

The competitive nature of cycling makes it essential for riders to employ optimal strategies based on their individual physical attributes to minimize the time required to cover the race course. The individual time trial events attract a diverse range of cyclists, including climbers, sprinters, and time trial specialists. Therefore, we establish a model that optimizes the power output of a specific rider type to minimize the total time it takes to traverse the entire course.

1.2 Problem Statement and Analysis

To achieve the objectives outlined in Section 1.1 and provide riders and the Directeur Sportif with an idea of an optimal pacing strategy, we must complete the following:

1. **Establish an optimal pacing strategy model:** We first establish a physical model of the velocity of the rider based on the power that they output. We establish Critical Power (CP) which the riders can maintain for an indefinite period. When the rider applying greater power than the CP threshold, the rider is becoming fatigued and losing energy that they can utilize for motion. Once this energy reaches 0, the bicyclist returns to CP. The rider may "recharge" the energy in their tank by riding below CP for extended periods. To determine an optimal pacing strategy, we use this model in conjunction with a genetic algorithm to optimize power output along the course.

2. **Apply the model to various time trial courses:** We define power profiles for a time trial specialist who has an endurance focus and a puncheur who are best suited to tackle short but steep climbs. We apply our model to both male and female athletes in these cycling categories using the Olympic time trial course at Tokyo, the UCI World Championship course in 2021, as well as a custom course outlined below.

3. **Sensitivity analysis for weather and deviations from target power distribution:** We analyze our model's sensitivity to perturbations in weather (wind velocity) and rider power output deviations from the target power distribution.

4. **Team time trial expansion:** We consider a modification to our model where we reduce air resistance acting on the fourth rider, while the five other riders absorb the brunt of the air resistance load throughout the race, allowing the fourth rider to conserve energy.

2 Power Profiles

In order to define an accurate power profile for a rider, we used a first-order ordinary differential equation (ODE) to model power output over time. This ODE captures the physical constraints of continuous power output over time and uses the parameters outlined below.

2.1 Power Model Parameters

Table 1: Parameters used in the power profile ODE

Symbol	Variable	Units	Description
$P(t)$	Power output	W	Rider power output as a function of time
t	Time	s	Time
r	Rate constant	–	Determined by physical attributes of rider
c	Scaling parameter	–	Scaling parameter (constant)
$P_{\max}$	Maximum power	W	Maximum power output
$\frac{dP}{dt}$	Power rate of change	$\frac{W}{s}$	Time derivative of power output

The power curve model is given by the following equation [3]:

$$\frac{dP}{dt} = rP(t)\left(c - \frac{P(t)}{P_{\max}}\right) \tag{2.1}$$

This model accounts for the maximum power output of a given rider to determine how much power they exert over time based on their physical characteristics. This is determined by fitting the model to real-life data recorded during similar races.

2.2 Fitted Power Profile

To fit the power model, we used power output data of various professional cyclists from Strava. We selected Mathieu Van der Poel [7], who is a puncheur, Jonas Vingegaard [6], and Demi Vollering [5]; the latter two are excellent time trial specialists. Using data from their respective Strava accounts, we were able to fit our models. Figure 2 displays an example of the optimized model compared to the power data we collected from Strava.

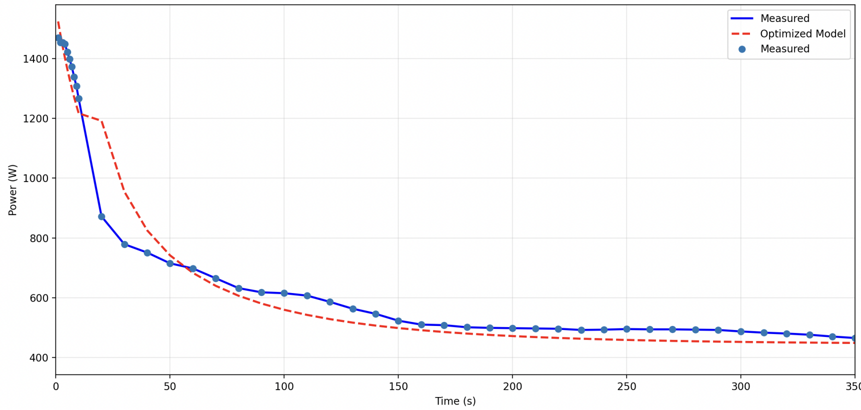


Figure 2: Mathieu Van der Poel power curve data compared to model

The final three power curves for all three riders are displayed in Figure 3. These profiles will be used in subsequent models as starting parameters for critical power and maximum power for these riders.

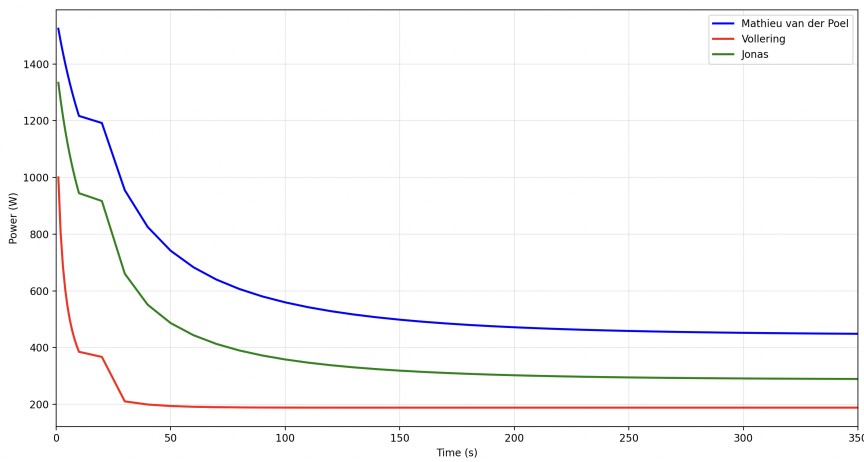


Figure 3: Power Curves for Van der Poel, Vingegaard, and Vollering

A puncheur has very high initial power output as they specialize in short and steep climbs, expending a lot of energy in a short period of time [8]. A time trial specialist can typically hold power for longer durations. In Figure 3, Van der Poel has a much higher maximum power and initial power compared to the two time trial specialists. Both time trial specialists have a high critical power, with a lower maximum power. It is important to note that, typically, the power curves for time trialists and a puncheur are closer together, but Van der Poel is currently one of the strongest cyclists in the world, which impacts our power profile figure.

From these power profiles, we can obtain important information such as critical power CP (the power a cyclist can sustain indefinitely) from the power profile's asymptote, the maximum power output P_{max}, and the amount of energy in a cyclist's "tank."

3 ODE Model and Physics Simulation

3.1 Assumptions

1. Assume wind is constant and follows a constant direction vector field across the courses. In our tests, we assume the wind speed is 10 m/s and the effective wind vector varies as the rider changes their direction.

2. Assume rolling friction is constant with a coefficient of 0.004.

3. Assume constant air density of $1.225 kg/m^3$.

4. Assume a drag coefficient and rider's frontal area multiply to equal a constant coefficient of $0.3m^3$.

3.2 Notations

We use superscripts to denote time-dependent variables such as power output at given time-steps, where P^n_{output} represents the power output at time-step n.

3.3 ODE Model and Underlying Physics

The core of our model relies on the physical principles of motion. At a specified velocity at a timestep (v^n), wind velocity contribution (v_{wind}), and grade, we compute the resistances that the rider is facing and subtract these from the power they are outputting. The losses the rider assumes come as a result of three main detractors: Air resistance, rolling friction, and track grade. The forces associated with these resistances are computed as follows:

$$\text{Rolling resistance force:} \quad F^n_{\text{rolling}} = C_{\text{rr}} \, M_{\text{total}} \, g \quad [\text{N}], \tag{3.1}$$

$$\text{Grade (slope) force:} \quad F^n_{\text{grade}} = M_{\text{total}} \, g \, \sin\big(\arctan(\text{grade})\big) \quad [\text{N}], \tag{3.2}$$

$$\text{Aerodynamic drag force:} \quad F^n_{\text{aero}} = \frac{1}{2} \rho_{\text{air}} \, C_d A \left(v^n + v_{\text{wind}}\right)^2 \quad [\text{N}], \tag{3.3}$$

These values are then used to compute the necessary power that is lost by the rider in order to overcome the resistive forces.

$$\text{Total resistive power:} \quad P^n_{\text{losses}} = v^n \left(F^n_{\text{rolling}} + F^n_{\text{grade}} + F^n_{\text{aero}}\right) \quad [\text{W}], \tag{3.4}$$

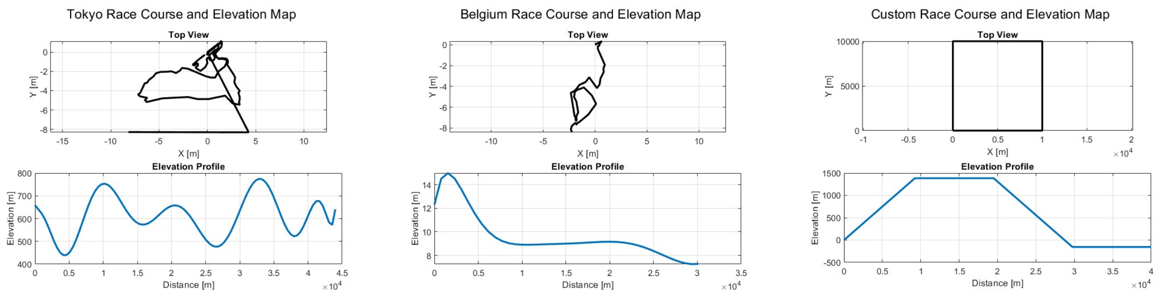
$$\text{Net power available for acceleration:} \quad P^n_{\text{move}} = P^n - P^n_{\text{losses}} \quad [\text{W}], \tag{3.5}$$

$$\text{Acceleration:} \quad a^n = \frac{P^n_{\text{move}}}{M_{\text{total}} \, v^n} \quad [\text{m/s}^2]. \tag{3.6}$$

After computing the acceleration for the new time step, we integrate using forward Euler to compute the velocity and distance along the track with which the rider enters the next time step.

$$v^{n+1} = v^n + \Delta t(a^n) \tag{3.7}$$

$$d^{n+1} = d^n + \Delta t(v^{n+1}) \tag{3.8}$$



(a) Tokyo, Japan course (b) Flander, Belgium course (c) Custom test course

Figure 4: Our three test courses

3.4 Courses

From published resources about the track profiles at the 2021 Tokyo Olympics and the 2021 UCI World Time Trials in Flander, Belgium, we constructed race-course matrices, discretizing the track into a set of N points in 2D space. Separately, we did high-order polynomial interpolation over the vertical track profiles in order to calculate the grade of the course at each of the N nodes. We also constructed a square test course with a grade 15 incline along the first stretch, a flat second stretch, a grade 15 decline along the third, and a flat fourth stretch returning to the starting location.

3.5 Wind

We treat wind as a vector field that the cyclist must overcome. We compute the net wind effect as the dot product between the wind and biker's direction, shown in Figure 10.

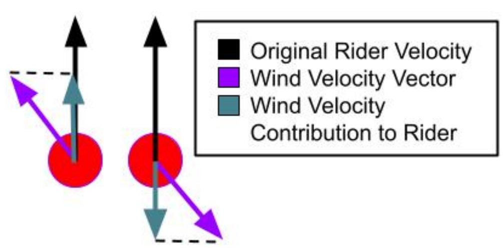


Figure 5: Wind Effect on Rider

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4 Skiba Energy Store Model

The Skiba Model is a standard algorithm used to model how a cyclist's power output above their critical power (CP) affects their anaerobic energy 'tank' capacity. An empty tank represents the complete exhaustion of the cyclist, meaning they cannot output any power exceeding their CP until they recover their tank energy by outputting less power than the

CP. The Skiba model acts as a biologically realistic constraint on the cyclist's output power over the course of the race.

4.1 Skiba Model Parameters

Table 2: Skiba Model Parameters

Variable	**Symbol**	**Unit**	**Description**
Critical power	CP	Watts	The amount of power the cyclist can output indefinitely.
Power output	P	Watts	Current power output.
Power difference	D_{CP}	Watts	Difference between P and CP.
Tank energy	W'_{tank}	Joules	Amount of the available energy the cyclist can expend on output power above CP.
Maximum tank storage	W'_{max}	Joules	Maximum available energy the cyclist can store.
Maximum power output	$P_{\max}$	Watts	Maximum amount of power a cyclist can output.
Recovery time constant	τ_W	seconds	The time constant used to scale the cyclist's tank (W') recovery rate.

When the cyclist expends power above CP, they lose tank energy–i.e. W'_{tank} decreases–at a rate directly related to the difference between output power and CP:

$$\frac{dW'_{tank}}{dt} = P(t) - CP \tag{4.1}$$

Conversely, when the cyclist recovers by exerting less power than their critical power, they increase W'_{tank} according to the equation

$$W'_{tank} = W'_{max} - \int_0^t (P(t) - CP)e^{-\frac{t-u}{\tau_W}}\,dt \tag{4.2}$$

$$\tau_W = 546e^{-0.01(P(t)-CP)} + 316 \tag{4.3}$$

where the recovery time constant τ_W depends on the difference between the current power output and CP and is experimentally found to have a minimum time of 316 seconds for a typical athlete.

We calculate W'_{max} according to equation (4.1) by multiplying the different between the amount of power each cyclist can exert for 25 seconds and their CP by the duration (25 seconds).

This equation models that the recovery time decreases as the recovery power drops further below CP [4].

5 Genetic Algorithm Power Output Optimizer

To optimize the cyclist's power output over a given race course, we develop a genetic algorithm (GA) that optimizes cyclist power output at each spatial node along the course by evaluating the fitness (finishing time) of a "generation" of cyclists, and allowing the fastest cyclists to pass on their "genes" to the next cyclist generation.

5.1 Decision-Making Process

Each cyclist calculates their output power according to their "genome," or parameters that act on a state vector (Table 3) describing the cyclist's state as they progress along the course. We normalize the state vector variables between $[-1, 1]$ or $[0, 1]$ to improve the GA's performance. We also divide the course into 25 segments and only permit the GA to select one target output power per segment. We found that this segmentation accurately reflects the decision-making of human cyclists who don't decide the power to exert at every meter of the course, but rather choose a given power to exert over the course of several hundred meters. This also helped optimize the GA by increasing the significance of its individual choices and increasing the significance of early decisions, especially on longer courses such as Tokyo (44 km).

We combine these state variables into a state vector

$$s^n = \Big[\frac{P^n_{output}}{P_{\max}}, \frac{d}{d_{max}}, \frac{i^n_{segement}}{N_{segement}}, \frac{W'^n_{tank}}{W'_{max}}, \frac{P^n_{loss}}{CP}, \frac{v^n_{wind}}{v_{wind,max}}, \frac{G^n}{G_{total}}, \frac{G^n_{u,remaining}}{G_{total}}, \frac{G^n_{d,remaining}}{G_{total}}\Big]^T$$

The GA optimizes its genome, which in our case comprises a set of parameters $\alpha = [\alpha_1, \alpha_2, ..., \alpha_9]^T$ that controls the power output at each timestep based on a given state vector s^n through the equation

$$\begin{aligned} P^{n+1}_{sum} &= \alpha^T s \\ P^{n+1}_{optimal} &= \frac{P_{max}}{1 + e^{-P^{n+1}_{sum}}} \end{aligned} \tag{5.1}$$

where the sigmoid expression $\frac{P_{max}}{1+e^{-P_{sum}}}$ is chosen to normalize the output power between 0 and P_{max} watts. To ensure biologically realistic final output power selection, we apply smoothing to the power output using a smoothing factor $\beta = 0.15$. This ensures the GA will not rapidly oscillate between dramatically different power outputs, which would be physically unrealistic.

$$P^{n+1}_{output} = P^n_{output} + \beta(P^n_{output} - P^{n+1}_{optimal}) \tag{5.2}$$

We also clamp the output power between P_{max} and 0 to ensure physically meaningful behavior. Moreover, if the rider's W'_{tank} empties to 0, we constrain the rider's maximum power to CP–which the cyclist can sustain indefinitely–modeling aerobic exhaustion and ensuring they cannot indefinitely exert power above their CP.

Table 3: State vector parameters input into the GA control model

State Variable	Symbol	Range	Description
Power output	$\frac{P^n_{output}}{P_{\max}}$	$[0, 1]$	Current power output scaled by the maximum power output.
Distance traveled	$\frac{d}{d_{max}}$	$[0, 1]$	Fraction of the total remaining distance, providing anticipatory pacing behavior.
Segment index	$\frac{i^n_{segement}}{N_{segement}}$	$[0, 1]$	Segments traveled, normalized by the total number of segments.
Tank energy	$\frac{W'^n_{\text{tank}}}{W'_{max}}$	$[0, 1]$	Remaining energy relative to the total available work above critical power at the start of the race.
Power losses	$\frac{P^n_{\text{loss}}}{CP}$	$\sim [-1, 1]$	Mechanical power losses due to rolling friction, aerodynamic drag, and gravity. Note that we normalize over CP to improve GA performance.
Wind velocity	$\frac{v^n_{wind}}{v_{wind,max}}$	$[-1, 1]$	Wind velocity relative to the maximum wind velocity along the course.
Current grade	$\frac{G^n}{G_{total}}$	$[-1, 1]$	Current normalized grade relative to the maximum grade.
Total remaining uphill	$\frac{G^n_{u,remaining}}{G_{total}}$	[0, 1]	Sum of all remaining uphill grades divided by total uphill on course.
Total remaining downhill	$\frac{G^n_{d,remaining}}{G_{total}}$	[0, 1]	Sum of all remaining downhill grades divided by total downhill on course.

5.2 Ensemble Optimization

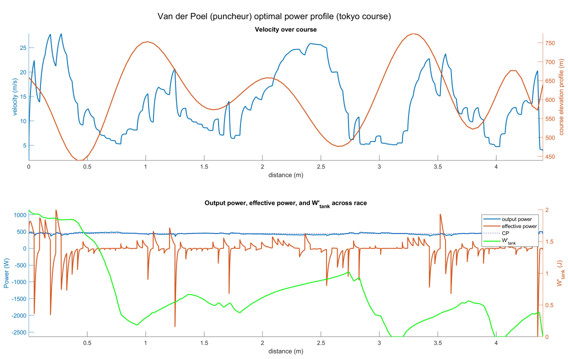
The simulation for a given course map is initialized with a generation of $N = 100$ cyclists, each with parameters randomly selected from a normal distribution within $[-1, 1]$. Each cyclist time-steps through the race course until they finish, calculating the optimal power output at each subsequent timestep according to their genome and time-dependent state vector, whose parameters are given in Table 3. At each time-step, the course rolling resistance, grade, and aerodynamic drag forces are summed to represent a total loss power (3.4), which is subtracted from the cyclist's output power to yield a net power and acceleration (3.6), (3.8). After each cyclist finishes, their fitness is calculated by their finish time. The 10% fittest (lowest fitness scores) cyclists survive to the next generation and the 50% fittest cyclists randomly reproduce with each other to produce the other 90% of next generation. Each "child" cyclist receives a random 50% of each "parent's" genome. Thus, the fittest power-optimizing parameters are passed on to each subsequent cyclist generation.

We simulated Van der Poel (puncheur), Vingegaard (time-trial specialist), and Vollering (time-trial-specialist) on three different courses: the 2021 Olympics Time Trial Course in Tokyo, Japan; the 2021 UCI World Championship in Flanders, Belgium; and a custom square-shaped course (4 90° turns) with ±15% grades on two of the four square legs. The GA optimized 100 cyclists per generation over 100 generations to obtain the optimal power curves.

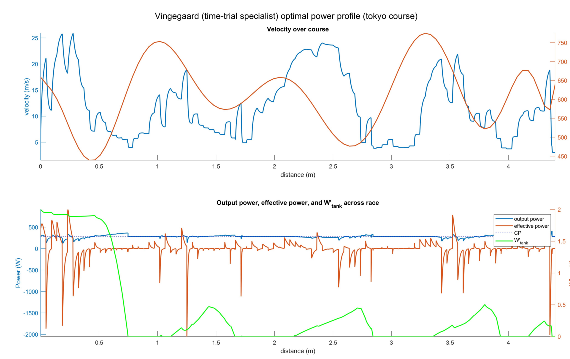
5.3 Target Power Distribution Results

Below we include the numerical results for the cyclist profiles of Van der Poel (puncheur), Vingegaard (time-trial specialist), and Vollering (time-trial specialist) on each of the three courses. We include the course grade in orange and the cyclist's velocity in blue on the top graphs and their output power, effective power accounting for losses, and their W'_{tank} in green on the bottom graphs.

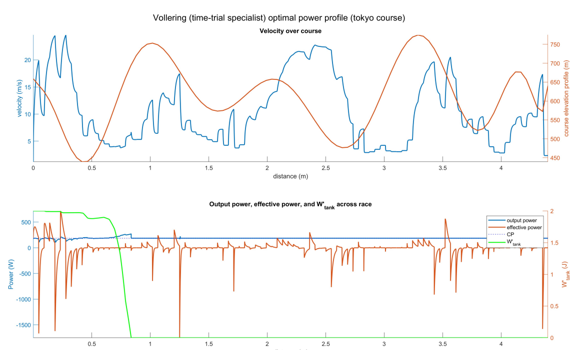
5.3.1 Tokyo, Japan 2021 Olympic Time Trial course



(a) Van der Poel



(b) Vingegaard



(c) Vollering

Figure 6: Optimized power distributions on the Tokyo Olympic time trial course.

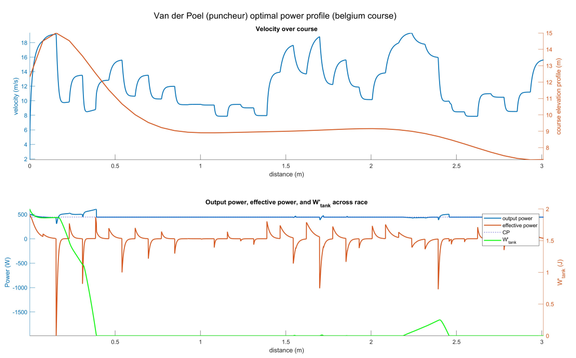
As our results demonstrate, Van der Poel, the puncheur, performs the best on the 2021 Tokyo course due to his ability to exert short, powerful bursts of speed on this course's hilly terrain. The time's included in Table 6 are relatively consistent with the actual finishing times of cyclists in the 2021 Tokyo Olympics.

Table 4: Finishing Times for Tokyo 2021 Olympic Time Trial Course

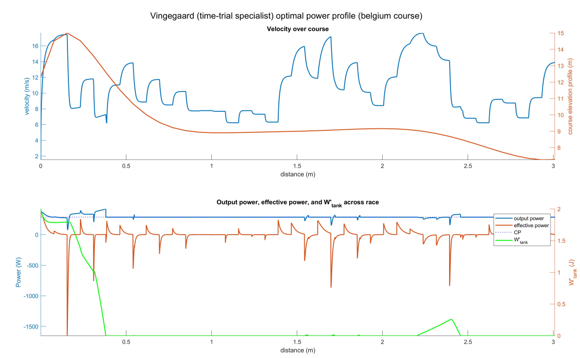
Rider	**Finishing Time (hh:mm:ss)**
Van der Poel (Puncheur)	01:08:24
Vollering (Time-Trial Specialist)	01:42:09
Vingegaard (Time-Trial Specialist)	01:22:42

Regarding racer strategy, Figures 6a, 6b, and 6c show that due to the course's hilliness, the racers choose to expend most of their tank on the uphill because they can recover much of it on the subsequent downhill sections. This can be visualized by the oscillating motions of W'_{tank} in both Van der Poel's and Vingegaard's power distribution graphs.

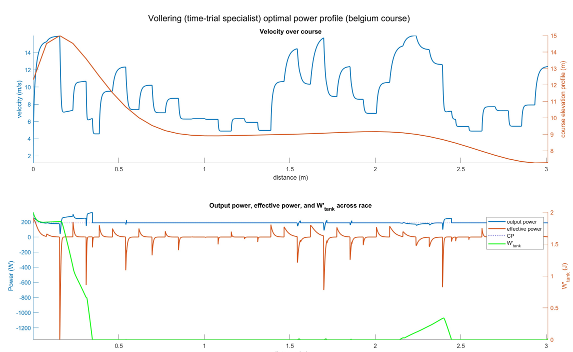
5.3.2 Flanders, Belgium 2021 UCI World Championship time trial course



(a) Van der Poel



(b) Vingegaard



(c) Vollering

Figure 7: Optimized power distributions on Flanders 2021 UCI World Championship course.

Table 5: Finishing Times for 2021 UCI World Championship Time Trial Course

Rider	**Finishing Time (hh:mm:ss)**
Van der Poel (Puncheur)	00:48:29
Vollering (Time-Trial Specialist)	01:02:08
Vingegaard (Time-Trial Specialist)	00:51:31

While the puncheur Van der Poel still beats both time-trial specialists Vingegaard and Vollering in this course, Vingegaard and Vollering both achieve much closer times to Van der Poel, likely due to the fact that they are time-trial specialists with high long-term stamina and Van der Poel specializes in short sprints. This partially makes up for the fact the Van der Poel is simply a stronger overall cyclist, bringing their finishing times closer together and evening the playing field slightly.

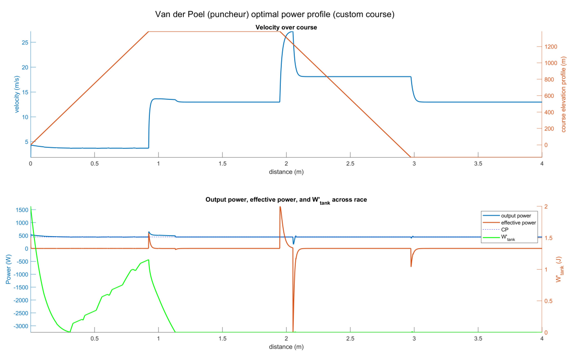
Strategically, the optimal cyclists choose to conserve energy on the initial uphill part, and use the entirety of their W'_{tank} on the downhill to overcome wind and gain speed for the remaining flat sections. Later in the race, they all decide to recover some of their energy to enable them to push for the last part of the race, demonstrated by the increase in velocity and decrease in W'_{tank} towards the end of the race.

5.3.3 Custom Course

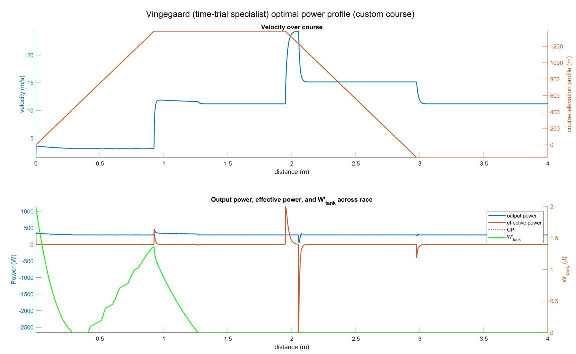
On this course, the optimized cyclists appear to choose to conserve and recover their W'_{tank} storage on the downhill segments, while also trying not to over exert themselves on the initial uphill stretch. This allows them to use the rest of their W'_{tank} on the flat sections and coast on the downhill portion in the latter half of the race.

Table 6: Finishing Times for Our Custom-Designed Course

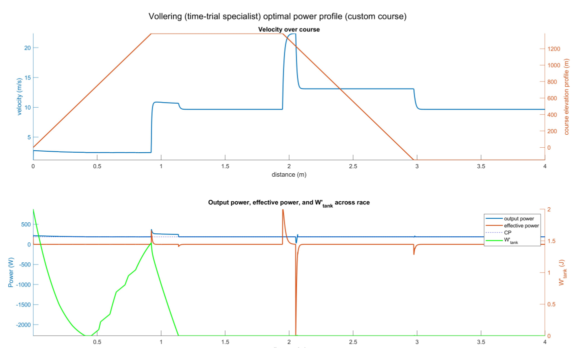
Rider	**Finishing Time (s)**
Van der Poel (Puncheur)	01:16:22
Vollering (Time-Trial Specialist)	01:51:25
Vingegaard (Time-Trial Specialist)	01:30:51



(a) Van der Poel



(b) Vingegaard



(c) Vollering

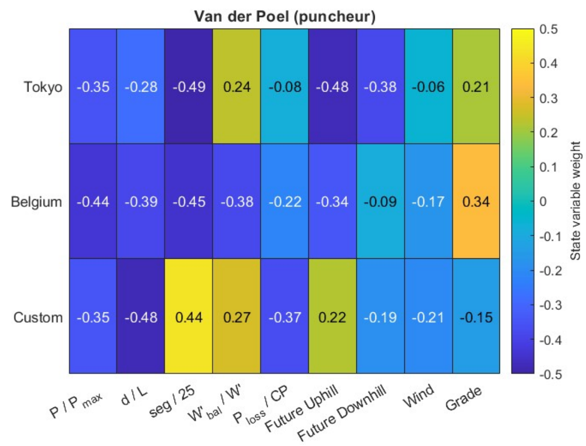
Figure 8: Optimized power distributions on the custom-designed course.

5.4 Genome Analysis

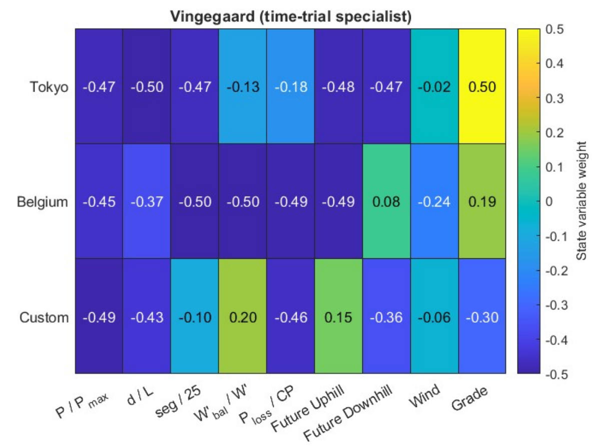
Table 7: Optimized genome weights for all riders and courses

State Variable	Van der Poel (Puncheur)			Vollering (TT)			Vingegaard (TT)		
	Tokyo	Belgium	Custom	Tokyo	Belgium	Custom	Tokyo	Belgium	Custom
$P_{\text{out}}/P_{\text{max}}$	-0.354	-0.492	-0.346	-0.306	-0.498	-0.189	-0.473	-0.483	-0.493
Distance / Total Distance	-0.279	-0.366	-0.479	-0.401	-0.458	-0.476	-0.498	-0.375	-0.434
Segment Index	-0.495	-0.380	0.439	-0.069	-0.166	-0.284	-0.468	-0.360	-0.097
W'_{bal}/W'	0.236	-0.491	0.266	-0.462	-0.500	0.144	-0.132	-0.498	0.198
P_{loss}/CP	-0.079	-0.480	-0.367	-0.096	-0.500	-0.446	-0.181	-0.491	-0.458
Future Uphill	-0.476	-0.373	0.224	-0.429	-0.106	0.070	-0.480	-0.461	0.153
Future Downhill	-0.382	0.498	-0.187	-0.493	0.490	-0.253	-0.466	0.498	-0.363
Wind Speed	-0.061	-0.250	-0.206	-0.103	-0.307	-0.362	-0.023	-0.238	-0.064
Course Grade	0.212	-0.019	-0.148	0.137	0.087	-0.293	0.496	-0.027	-0.297

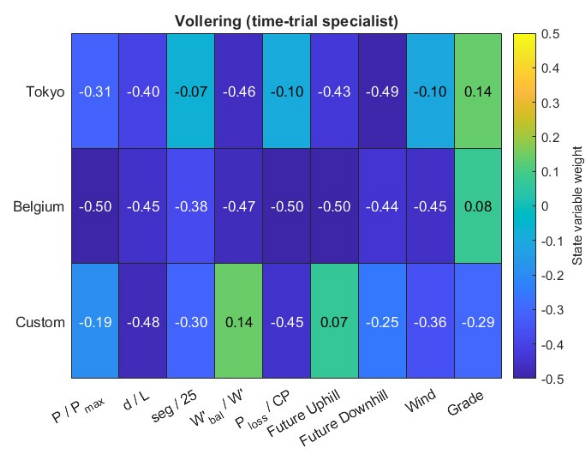
Our results in Table 7 and Figures 9a, 9b, and 9c demonstrate that the most important features for optimizing output power included current output power (P/P_{max}), distance and segments traveled (d/d_{max}), current total losses P_{loss}/CP, and remaining uphill. Conversely, both grade- and wind-induced losses were less significant factors in the power distribution optimization process, though the grade was much more significant in the hillier Tokyo and custom courses. Additionally, the wind loss was more significant in the Belgium and custom courses, likely because it was not overshadowed by the extreme hilliness of Tokyo.



(a) Van der Poel



(b) Vingegaard



(c) Vollering

Figure 9: Heatmaps showing each rider's optimized genome weight across courses.

6 Sensitivity Analysis

6.1 Wind Speed Sensitivity

To conduct a sensitivity analysis on the impact of varying wind speeds on the finish time for each rider, we varied wind speeds for each rider. Using the genetic algorithm, we obtained the predicted finishing time for the course (Tokyo in this case) for each rider under each wind speed. Outcomes are displayed in Figure 10.

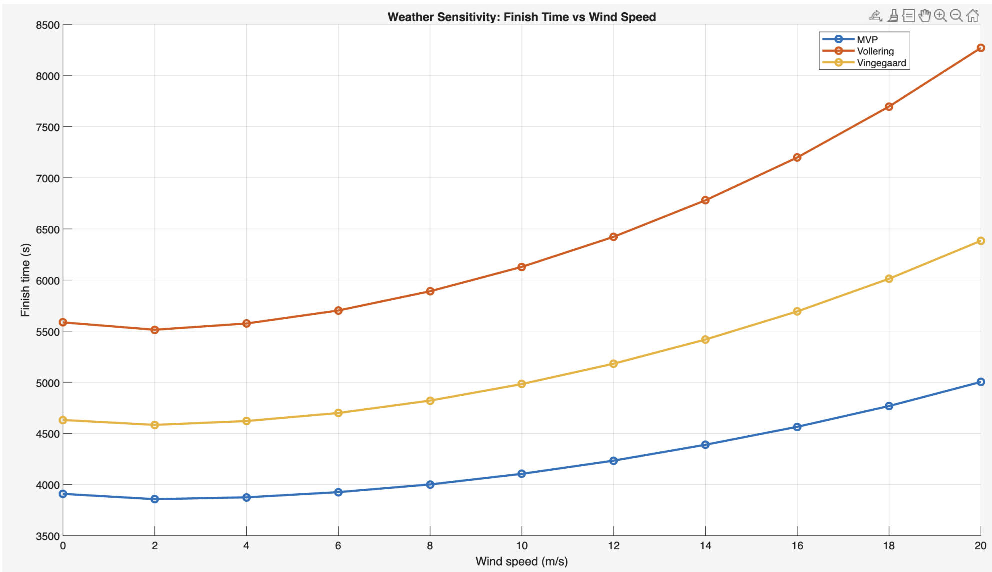


Figure 10: Wind Speed and predicted finishing time

We observe that increased wind speed impacts the two time trialists far more than it impacts van der Poel (the puncheur). Van der Poel's finishing time increases, but at a more gradual rate. These results are consistent with our expectations, given the cyclists' profiles. Since van der Poel specializes in short bursts of power, his superior strength should enable him to better cope with increased wind speed than Vollering or Vingegaard.

6.2 Rider Power Deviation Sensitivity

Because cyclists will almost certainly miss the target power distribution at various points along the course, we also conduct a sensitivity analysis on rider deviation from target power distribution. On each rider profile's optimized parameters, we time-step through the Tokyo race course and randomly perturb the output power according to a normal distribution centered at the optimal output power with standard deviations σ varying between 0.2 and 2. Results are shown in Figure 11

These results illustrate that the finishing times of all riders are somewhat sensitive to deviations from the optimal target power distribution. However, if most rider's stay within 0.6 standard deviations of the target power distribution, their finishing time will only increase marginally (though Van der Poel's time is more sensitive to deviations that Vollering and Vingegaard).

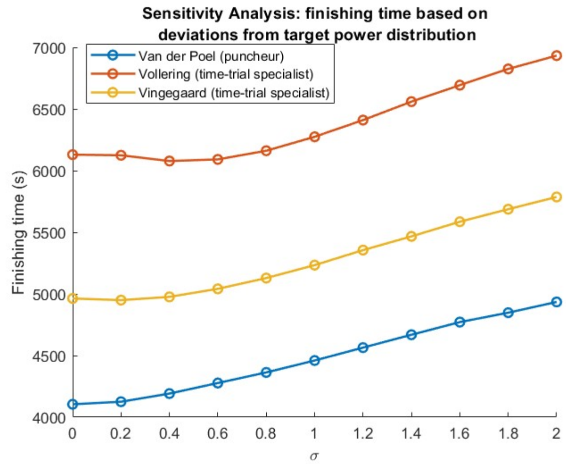


Figure 11: Sensitivity analysis on rider deviation from target power distribution on 2021 Tokyo course.

7 Extensions

When considering team trials, the primary concern is the effect of drafting on the power output of the riders. "Follower" riders in the slipstream of the pack leader can receive significantly less air resistance. Simply reducing the air resistance of a follower without capping their velocity in the model may cause the simulated follower to overtake the pack leader, thus subjecting them to full air resistance. To extend our model to team trials, we would designate a pack leader to receive full air resistance for a certain portion of the track. Other riders, whose velocities are capped by the pack leader, face reduced air resistance, allowing them to save energy. We would allow simulated riders to take shifts leading when we have determined that a proportional amount of the lead riders energy to the distance along the course has been spent. This would allow the pack to travel faster overall because each individual would save energy when riding behind the leader and thus be able to exert more output power when they take their turn as the speed-dictating leader.

8 Strengths and Weaknesses

8.1 Strengths

The Genetic Algorithm:

1. **Interpretable:** the GA model optimizes and outputs parameters that are generally interpretable because they act on specific, physically meaningful state vector variables.

2. **Explores parameter space effectively:** the GA's multi-agential nature allows the algorithm to explore the parameter space thoroughly. Moreover, its gene selection and mating process incentivizes exploration of more promising parameters, allowing it to simultaneously explore the parameter space while focusing its computational energy on

developing the most promising genomes and effectively ignoring the blatantly wrong parameter combinations.

3. **Robustness:** Our algorithm is robust and easily extendable to other race courses and rider profiles.

8.2 Weaknesses

The Genetic Algorithm

1. **Slow convergence:** the GA is slow to converge and may not reach find the absolute most optimal parameter set, even with 100 generations with 100 cyclists in each generation.

2. **Limited decision-making capability:** the GA is limited to making decisions based on its 9 parameters that can only linearly scale each state vector variable and act the same at every time-step. This means that the model cannot capture relationships between the state variables. If we wanted to mitigate this weakness, we could add parameters for each time step and create a neural network of interconnected parameter weights that would allow us to capture these time-dependent state variable interactions. However, this would also make the model much more complex and less explainable due to the significant increase in tunable parameters. It would also require significantly more data that would be potentially prohibitively time-consuming and expensive to collect.

9 Letter to Directeur Sportif

Cher Directeur Sportif,

As cycling has progressed into the 21st century, athletes have increasingly benefited from advances in access to technology to enhance training and performance analysis to help them become better athletes. In cycling, these technologies allow for far more performance data collection, which can be used to help an athlete perform better. As you know, given the highly competitive nature of professional cycling, even a small gain in efficiency can be the difference between winning a race and placing outside the top 10.

To take advantage of advancements in technology, we have developed a model that integrates the physical characteristics of a cyclist, through data from their previous races, with publicly available race course data. This allows us to optimize a race strategy tailored to a specific rider's strengths.

Our model operates by first creating a power profile for the specific type of cyclist using historical data. Then we take into account how much power output impacts fatigue for a specific rider. Finally, we use a genetic algorithm that uses the cyclists' characteristics to simulate repeated traversals of the race course and changing power output strategies across generations to ultimately provide us with the optimal power output at each point on the course.

In Figure 12, we see the 2021 Olympic Time Trial course in Tokyo, Japan. In Figure 13, we see the power curve for Mathieu Van der Poel that we fitted to data obtained from Strava and used to design an optimal race plan for this specific time trial course.

Figure 12: 2021 Olympic Time trial course in Tokyo, Japan[1]

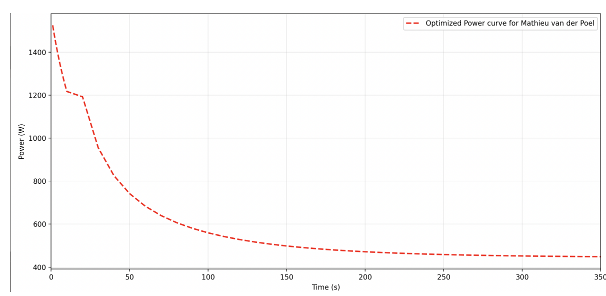


Figure 13: Mathieu Van der Poel Power curve

Tokyo is a course that has two main high peaks that must be climbed. As a puncheur, this plays to van der Poel's strengths as he can use his strength to attack these inclines. In

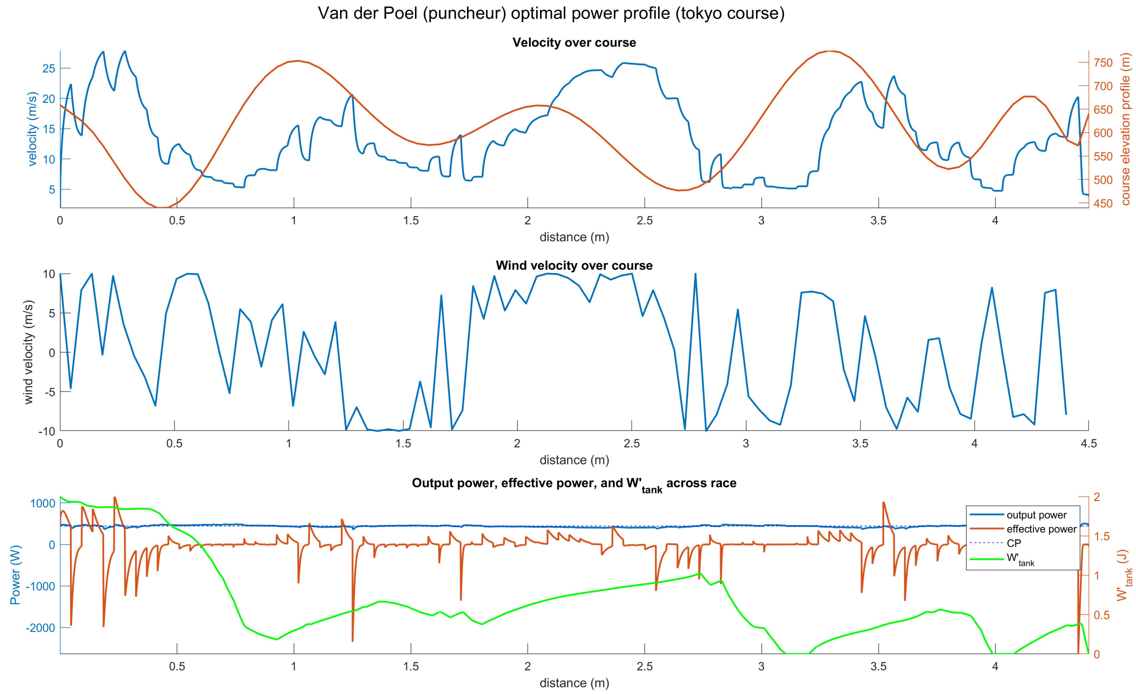


Figure 14: Optimized race plan for van der Poel

Figure 14, we see the optimal strategy that our algorithm has produced for van der Poel, given his characteristics and the track information available.

From our algorithm's optimal output, we see that van der Poel should use a significant amount of his energy on the four main climbs that occur on this course. Following the climbs, he must recover before expending the energy again. His velocity should slow as he climbs, but increase as he heads downhill.

Our model anticipates that if he follows the strategy outlined above, he will finish the race in 1 hour, 8 minutes. This was calculated taking into account both grade and wind displayed in the second graph in Figure 14. Moreover, if he stays within 0.6 standard deviations from a normal distribution centered at the target power distribution, his time will only increase marginally, as shown by our sensitivity analysis. Through further extensions to our model and more accurate weather data as the race approaches, we will be able to create an even more optimized plan for Van der Poel. For now, this is the optimized power output that we have curated using our model. We hope that our model can help cyclists of all ages improve their race times and ultimately become more competitive athletes.

Kind regards,

MCM Team

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