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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

Project 4:05: Optimizing USA Cycling’s Women’s Team Pursuit Gold

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Abstract. In Olympic cycling, the difference between earning a gold medal and not earning a medal is measured in fractions of a second. For USA Cycling’s women’s team pursuit squad, the 2023 World Championships in Glasgow, Scotland, highlighted a stark reality: the team placed sixth with a time of 4:12.684 and missed the qualification round for the bronze medal by 0.159 seconds. With the Paris 2024 Olympics approaching and the team falling to eighth place in the world ranking, the challenge was clear: reduce nearly seven seconds off the team’s performance in one year, setting an ambitious target of 4:05 for the gold. With limited funding compared with powerhouse nations such as Great Britain, Australia, and New Zealand, USA Cycling relied on operations research, machine learning, data analytics, race simulation, and targeted athlete development to bridge the gap. Armed with cutting-edge analytics and modeling, real-time performance tracking, and aerodynamic innovations, Project 4:05 aimed at optimizing every aspect of the team’s race preparation and strategy from initial goal setting to team selection to race day tactical planning. Through data-driven decision making, USA Cycling achieved what few thought was possible: a stunning eight-second reduction in time to capture Olympic gold with a time of 4:04.306.

Keywords: Edelman Award • operations research • optimization • mixed-integer programming • sports analytics • Olympic cycling • team pursuit • aerodynamics

Introduction and Project Motivation

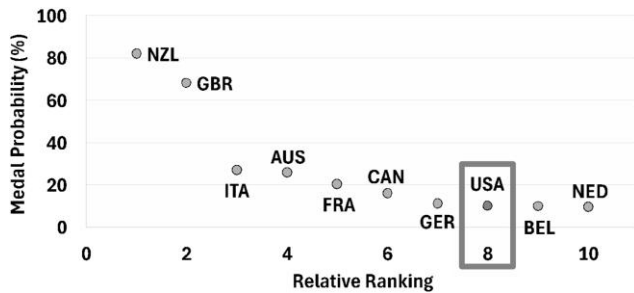
USA Cycling serves as the national governing body for competitive cycling in the United States, overseeing athlete development, event organization, and preparation for international competitions such as the Olympics and World Championships. The high-performance program within USA Cycling leverages expert coaching and staff, technical breakthroughs in equipment and aerodynamics, advanced data analytics, and tactical modeling to identify and maximize medal opportunities. This program’s funding is closely tied to performance outcomes, creating a cycle in which medal results directly influence future financial support and the organization’s ability to train elite athletes (Novy-Williams and Akabas 2024).

At the 2023 World Championships in Glasgow, Scotland, the women’s team pursuit squad underperformed, finishing in a time of 4:12.684, well below the top three teams and USA Cycling’s internal medal projections. As shown in Figure 1, the impact of the result and subsequent races dropped the women’s

team pursuit squad’s relative ranking to eighth place for the 2024 season with a corresponding Paris medal probability of only 10%. However, with the Paris 2024 games fast approaching, internal analysis identified this event as a unique opportunity. Although the New Zealand and Great Britain teams were dominant, there was potential for the U.S. team to improve significantly through data-driven athlete selection, an optimized race strategy, and achieving rider-specific physical and aerodynamic metric targets. Additionally, the relative weaknesses of teams ranked below the top two (New Zealand and Great Britain) provided further motivation to pursue aggressive, analytics-driven improvements, culminating in the launch of Project 4:05.

To achieve success in Paris, USA Cycling recognized the need to optimize every aspect of race execution, including rider aerodynamics, athlete selection, rider starting position, and rotation timing, to become medal competitive. Multiple factors drove this necessity. Competing nations with significantly larger budgets had access to superior facilities, year-round

Figure 1. Women's Team Pursuit Relative Ranking and Medal Probability by Country Based on Competitive Analysis and Modeling Internal to USA Cycling



coaching, and greater exposure to international competition, giving them a substantial advantage. As a result, USA Cycling required a high-return strategy focused on data analytics rather than increased funding. Exploratory analysis underscored the potential gains from improved rotation patterns and strategic rider drops, and moderate aerodynamic efficiency gains suggested a possible 1.5% performance improvement. To quantify this, USA Cycling created a simplified model comparing each rider's power requirements when leading versus recovering. By adjusting the target finish time, the model assessed whether the team possessed the necessary physical capacity to sustain the required lap speeds. Although this initial model did not capture every tactical nuance, it indicated that, based on 2023 World Championships data, the team could reduce its finish time from roughly 4:12 to 4:08, which would put it in gold medal contention. Yet, despite the U.S. squad's rich history of medaling in every Olympic women's team pursuit, the rapid advancement of other nations meant its chances

for success in Paris would remain low without significant optimized race planning and aerodynamic enhancements, both of which would become focal points of Project 4:05.

Team Pursuit: Track Cycling's Ultimate Tactical Race

Track cycling's women's team pursuit brings together team cooperation, aerodynamic precision, and sustained endurance in a race in which mere seconds can distinguish between a medal and obscurity. Team pursuit is held on a 250-meter indoor velodrome; the event requires each squad to complete four kilometers, which is equivalent to 16 laps, at speeds often exceeding 60 km/h or 40 mph. In the initial qualifying round, teams take the track one at a time, racing against the clock for the fastest times, which are used for subsequent round seeding. In subsequent rounds, two teams race on the track simultaneously starting on opposite sides of the track as shown in Figure 2. Although four riders begin the race, the team's official time is recorded when the third rider crosses the finish line. This four start, three finish format creates a strategic dimension: dropping one rider can sometimes raise the group's average velocity if it prevents overtaxing a weaker member, allowing the remaining trio to maintain a faster overall pace.

Physics at Play: Aerodynamic Drag

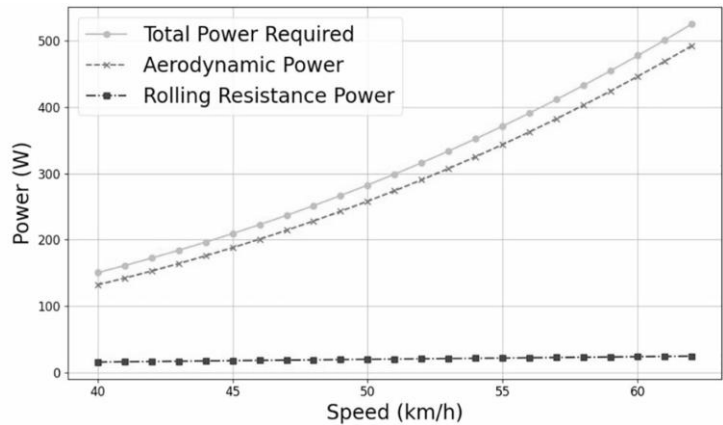
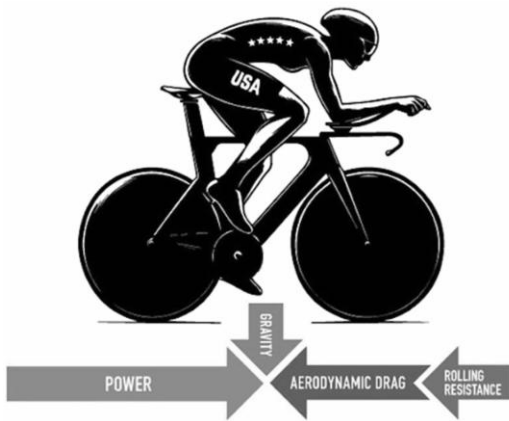
Because speeds frequently exceed 60 km/h, aerodynamic drag dominates the forces resisting the riders. Figure 3 shows the relevant forces acting on a cyclist for given speeds. As shown, the vast majority of the total power for a cyclist to travel at race speeds comes from aerodynamic drag (Debraux et al. 2011).

Figure 2. In Team Pursuit, Two Teams of Riders Starting on Opposite Ends of the Track Travel 16 Laps of the Velodrome for Four Kilometers (2.5 Miles)



Note. Four riders start, but only three are required to finish.

Figure 3. Forces Acting on a Cyclist in a Steady State



Note. Aerodynamic drag increases exponentially with speed.

Although rolling resistance increases linearly, it represents a small fraction of the total, especially given the smooth velodrome surface.

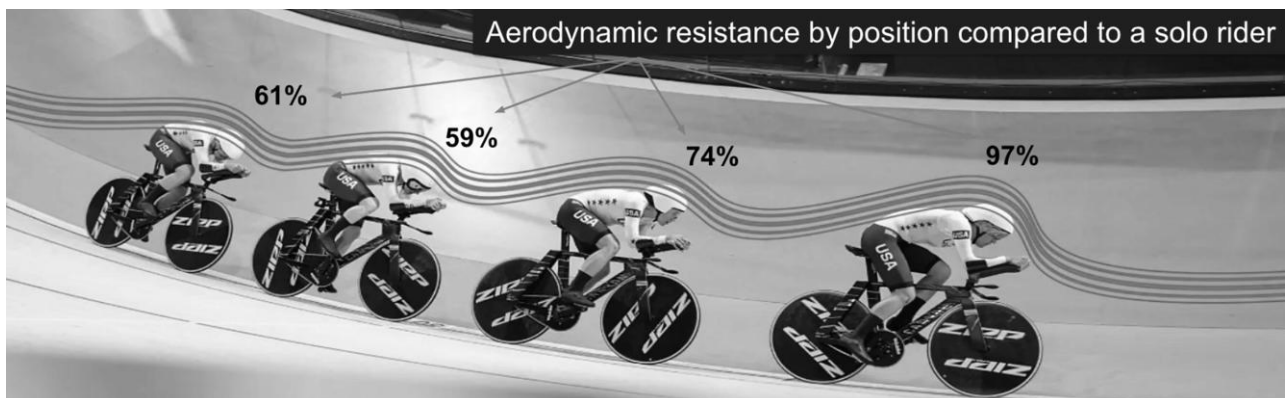
Even minor reductions in drag area can result in considerable power savings, accentuating the importance of positional changes and optimal rotation timing. Well-timed rotations prevent a single cyclist from becoming overly fatigued, enabling the team to maintain an optimal pace throughout the four-kilometer (2.5-mile) race.

The Physics Behind Drag and Power

The aerodynamic forces acting on cyclists follow well-established physical principles (see Appendix B for detailed equations). Key insights include that power requirements scale with the cube of velocity, making small speed increases very costly in terms of energy and drag area (the product of drag coefficient and frontal area) has a linear relationship with power requirements: a 10% reduction in drag area yields an approximately 10% reduction in the aerodynamic power needed to maintain the same velocity.

During the race, each cyclist's position significantly influences the team's energy expenditure and speed (Blocken et al. 2018). The lead rider (P1) experiences nearly full aerodynamic drag and, therefore, sustains higher power outputs. The second rider (P2) benefits from partial drafting (the aerodynamic advantage gained by following closely behind another rider, which reduces wind resistance) but still faces considerable energy depletion at race speeds, whereas the third and fourth riders (P3 and P4) gain the greatest aerodynamic shelter and can recover more effectively for subsequent rotations. Figure 4 shows the reduction in drag percentage and corresponding power required to maintain race speed in each position compared against that of a solo rider. Two notable aerodynamic effects emerge from these data: (i) the lead rider receives a slight reduction in power requirement compared with riding entirely alone because teammates behind her smooth the airflow and delay drag vortices (turbulent areas of air that increase drag), and (ii) the third rider (P3) is the most sheltered from

Figure 4. USA Cycling Deployed Aerodynamic Sensors to Measure Airspeed and Power Meters to Track Rider Force Output



Notes. This enabled the calculation of position-specific drag reductions (shown as a percentage compared with a solo rider on the track). These metrics then informed the subsequent optimization models.

aerodynamic impacts, whereas the fourth rider (P4) encounters minor turbulent vortices as the separated air merges behind the formation.

Game Plan: When to Rotate and Drop?

Determining how frequently to rotate the lead rider requires a delicate balance. If rotations are too infrequent, the lead cyclist may become dangerously fatigued, risking a sudden drop in power and speed. Conversely, rotating too often can waste energy and disrupt draft continuity because each new leader must increase power to maintain pace.

Another key strategic decision in the women's team pursuit is whether and when to drop a rider. Because only three riders need to cross the finish line for the team to record an official time, releasing a fatigued athlete at the right moment can boost the remaining trio's speed. However, dropping a rider too early sacrifices valuable drafting benefits in the midrace laps.

A carefully refined rotation plan can yield fractional second gains each lap, margins that are often decisive in a race determined by less than one second. As shown in Figure 5, in the steep banked corners of the track (located at the half-lap points), the lead rider has the option to move up the bank, then allow gravity to assist her momentum back into line. This technique helps reduce the transitioning rider's fatigue by adding a gravitational component to the forces needed to maintain speed.

Working Backward: Identifying the Target Time

Before officially launching Project 4:05, USA Cycling's analytics team needed to validate the endeavor's

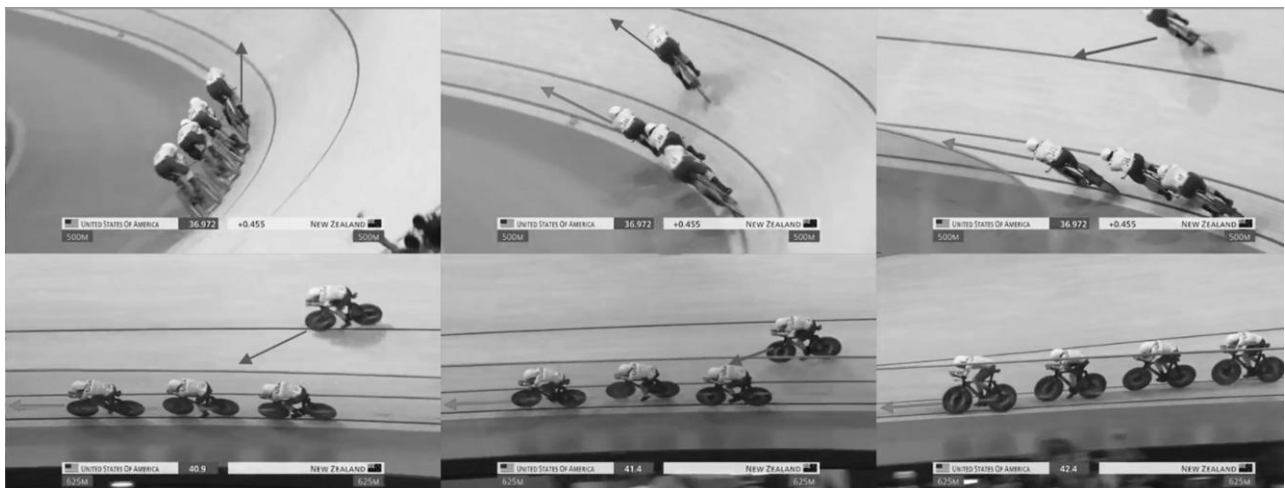
overall feasibility. Although the project was unnamed at that early stage, the group adopted an “Amazonian working backward” methodology to rigorously clarify goals and establish key metrics prior to committing resources to full model development and simulation design (Norton 2020). The key question was what finishing times would realistically position the team for a medal—potentially gold—at the Paris 2024 Olympics. Answering this became the North Star that guided subsequent project decisions. By leveraging a combination of machine learning and statistical methods, USA Cycling identified finishing times that were likely to earn a medal (finish in the top three) or claim gold under typical conditions anticipated for the Paris Olympic Games.

Not All Tracks Are Created Equal

To build a robust data set, the team collected results from previous Olympic Games and World Championships, including information on location, air density, and track type. Because air density varies significantly by altitude, temperature, and humidity, raw finishing times were not directly comparable across events. To address this, all results were normalized to a consistent air density of approximately 1.14 kg/m^3 , a value characteristic of Paris's velodrome conditions. This normalization removed confounding effects caused by extreme altitude or humidity, allowing more meaningful comparisons across different venues and years (Dwyer 2014).

The equation for this normalization is provided in Appendix D. As an example of this process, using the 2021 Olympic German team's world record time from Tokyo of 4:02.242 ridden at 1.09 kg/m^3 , normalized to typical Paris track air density conditions of 1.14 kg/m^3 , results in a time of 4:05.88.

Figure 5. Screen Captures Show the Lead Rider in Position P1 Peeling off from the Front as the Riders Navigate a Banked Corner During a Half Lap



Notes. This allows the rider in position P2 to pull through. The lead rider then uses gravity to slide back into line in position P4.

Forecasting Finishing Times

Using the normalized data set, the analytics team explored both traditional statistical regression and more advanced machine learning models to forecast finishing times for Paris 2024. Key predictors included air density, temperature, humidity, and year-over-year performance trends for each nation. Notable equipment innovations—such as newly introduced aerodynamic handlebars or advanced wheel designs—were also factored into the models. These predictors collectively provided a data-driven lens for estimating how fast the top competitors were likely to ride in 2024 under conditions similar to those expected in Paris.

Target Identified: The Project Finally Gets Its Name

Following calibration and validation, both predictive models converged on distinct time targets for medal contention as we show in Figure 6. The normalized regression analysis indicated a likely podium time of about 4:07 with a margin of uncertainty derived from the model's standard deviation. The analysis also suggested that gold medal performance would require a finish of 4:05 or better, assuming our normalized air density conditions and near-flawless execution. These benchmarks, 4:07 and 4:05, became the guiding metrics for every tactical, technological, and training decision that followed in Project 4:05.

Process Flow: Building Project 4:05

Having identified the estimated finishing times required for podium and gold medal contention, USA Cycling embarked on a multiphase plan to transform these performance benchmarks into concrete race-day strategies as shown in Figure 7. The foundation of this plan was the development of a comprehensive optimization model that could account for the various

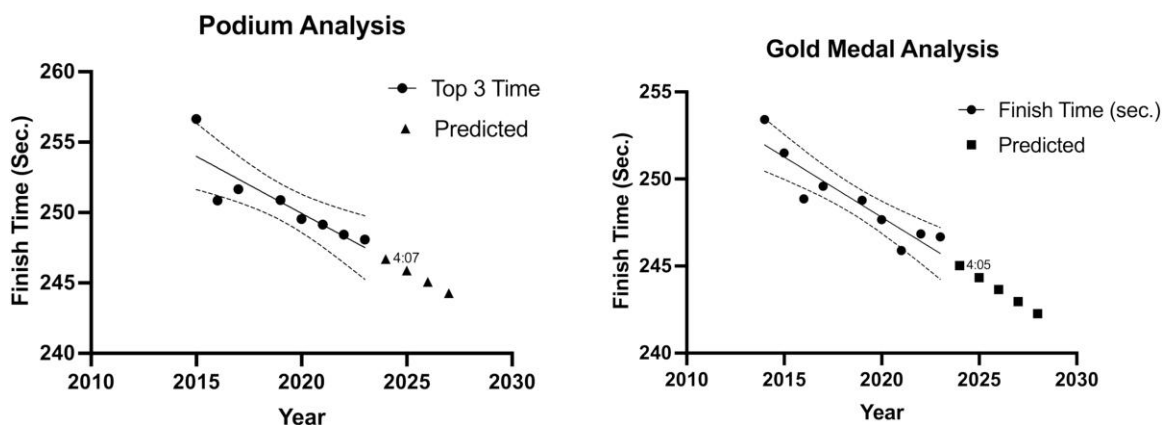
physical, tactical, and environmental factors affecting team pursuit outcomes. This model was intended not only to optimize how each athlete's strengths were utilized but also to highlight areas of improvement and potential weaknesses to mitigate.

The project began by confirming the North Star times derived from machine learning forecasts: essentially, what it would take to finish in the top three (earn a medal) versus what it would take to win. Next, we designed a dual-purpose advanced mixed-integer programming (MIP) framework, which can be exercised two ways: (i) to find optimal strategies or (ii) to evaluate scenarios by fixing the values of decision variables (i.e., used as a simulation tool). By adjusting factors such as rider order, rotation timing, and optimal points to drop the fourth rider, the team could identify strategies that minimized overall finishing time, making the most of each cyclist's distinct capabilities.

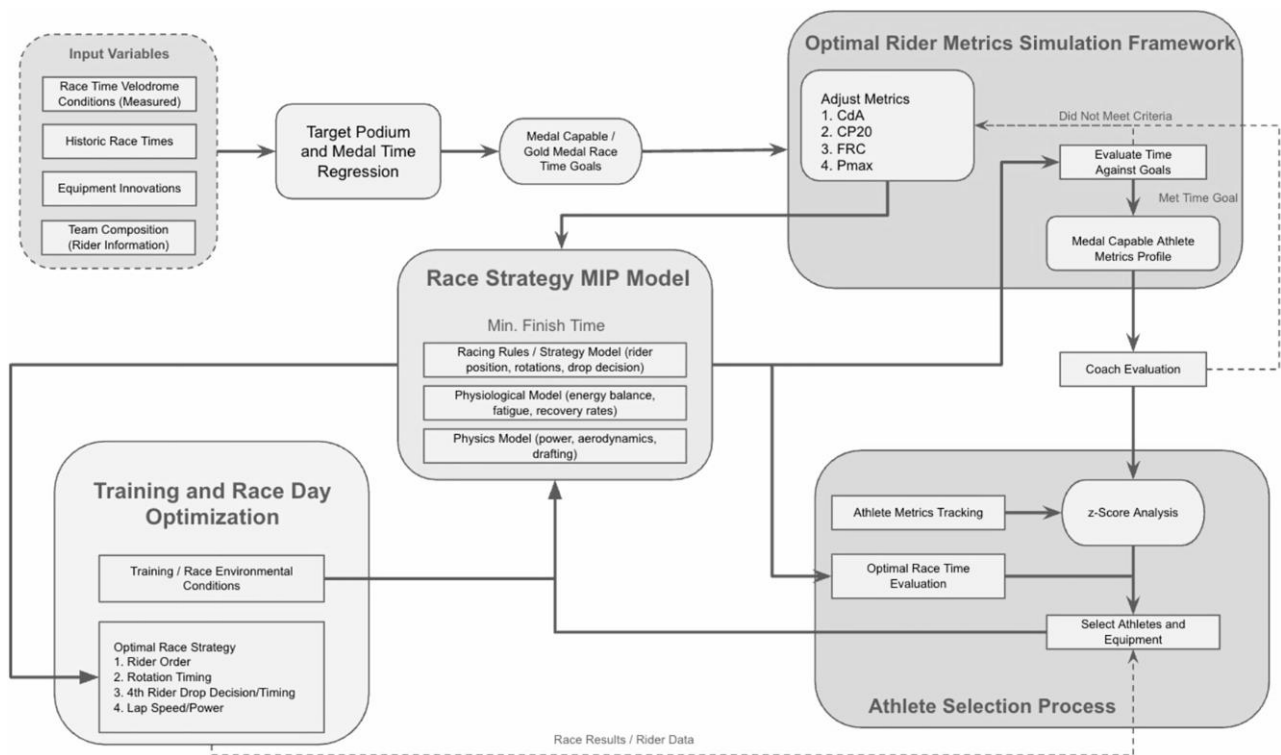
Once the optimization model's outputs were validated, the results flowed into the creation of hypothetical ideal athlete performance profiles. Although we discuss the specific physiological metrics (e.g., critical power or aerodynamics) in later sections, the general idea was to reverse-engineer the exact capabilities a team required to achieve a medal or a gold medal time. With these ideal profiles in mind, USA Cycling could monitor its existing athlete pool and chart each rider's development using a real-time tracking system based on standardized scores (e.g., a Z-score approach as we discuss in the "Data Tracking and Z-Scores" section). The iterative process of monitoring and selective training helped ensure that each cyclist moved closer to the ideal profile needed for collective success.

As the focus shifted to the final months before the competition, the tactical phase of the project took center stage. The optimization model was rerun with

Figure 6. Regression Analysis Based on Podium and Gold Medal Finish Times to Predict Target Finish Thresholds



Note. Podium and gold medal finish times from World Championships and Olympic Games were normalized to a consistent air density representative of Paris's velodrome conditions.

Figure 7. Process Flow for the Optimization Framework of Project 4:05

Notes. The diagram outlines the approach used to translate modeled medal target times into actionable race strategies. The model incorporates athlete-specific physiological and aerodynamic data, environmental conditions, and tactical considerations to minimize overall team pursuit time. The process iteratively refines strategies through MIP optimization, a team-defined scenario evaluation, and athlete performance tracking, ensuring alignment between predicted and real-world results leading up to the competition.

updated athlete data, producing increasingly refined recommendations for rotation schedules, lead orders, and the strategic drop moment. At each step, the model's outputs were validated in controlled training races, ensuring that real-world performance aligned with simulated results. This process continued right up to the event itself, allowing for last-minute adjustments if environmental conditions changed or athlete performance varied.

By the time the team reached the Olympic velodrome, the entire sequence—from initial goal setting to in-depth tactical refinements—had been validated through a mixture of high-fidelity simulations and rigorous on-track assessments. In effect, Project 4:05 leveraged cutting-edge analytics to create a feedback loop, guiding the squad seamlessly from early planning to final execution.

The Core of the Project: Optimization

The central element of Project 4:05 was the creation of a comprehensive model that balances both strategic elements (rotations, position assignments, and dropping a rider) and physiological considerations (power, fatigue, and aerodynamics) for the women's team pursuit. The model systematically evaluates

various configurations of riders and pacing strategies, ultimately pinpointing the race plan most likely to achieve a targeted finishing time.

Strategic and Physiological Drivers

Strategic Components

Rotation Scheduling. The MIP tracks which rider is in the front (P1) and how often positions rotate. Each rotation determines how many laps—or portions of a lap—a given rider will pull at the front, directly affecting pacing and energy expenditure. Because the team's overall pace depends heavily on who leads and when, this decision is central to optimizing final time.

Dropping. In women's team pursuit track racing, one rider may strategically leave the formation or drop. Our model designates this individual as the drop position (DP). Once the designated rider drops, the remaining three continue at race pace to the finish line. By optimizing when the drop occurs, teams can prevent excessive fatigue and sustain a higher speed because the rest of the formation can maintain a more efficient pace once the tiring rider has exited.

Speed Segments. Each lap is subdivided into smaller intervals (e.g., half laps or quarter laps) so that the

MIP can accommodate varying speeds and transition points, such as accelerating immediately after a rotation.

Physiological Components

Aerodynamic Profile (Coefficient of Drag Area (CdA)).

Each rider's CdA influences how much power is required to sustain a specific speed. In positions behind the leader (P2, P3, P4), the effective drag area is substantially reduced because of drafting benefits, making rider order a key factor in energy conservation.

Critical Power (CP20). CP20 is the maximum average power a rider can sustain for 20 minutes. Staying at or below this threshold helps conserve anaerobic energy reserves, also known as functional reserve capacity (FRC; as discussed in the next paragraph), thus delaying fatigue. Conversely, consistently riding above CP20 accelerates the depletion of these reserves and leads to quicker exhaustion.

FRC. FRC represents the pool of anaerobic energy available for bursts above CP20. In this model, we permit a biexponential reconstitution of FRC during lower intensity segments, thereby reflecting the fast and slow recovery processes that laboratory testing has shown to be key. Each athlete's fast and slow recovery rates differ based on laboratory data and historical race performance as we discuss in more detail below.

Acceleration Power (PMax). Peak power output (PMax) is especially important at the start of the race and whenever a rider transitions to the front. Some riders excel at high-power burst efforts, making them ideal for high-intensity pulls, particularly during the initial launch in P1.

Biexponential Energy Reconstitution. Accurately modeling energy reconstitution proved essential for capturing real-world athlete performance (Chorley et al. 2023). Laboratory data revealed that, after depleting anaerobic energy stores, riders regain FRC via two distinct recovery pathways: a fast component and a slow component. Each cyclist's rates for these components, denoted τ_{fast} and τ_{slow} , are determined through the following:

- i. Controlled laboratory testing. Athletes undertake repeated intervals above CP20 with variable-length rest periods. The speed at which they can again sustain high power yields insight into both fast and slow recovery rates.
- ii. Race or training analysis. Historical power data from actual races and intense training sessions confirm and refine laboratory-derived parameters, linking them to performance in real-world conditions.

In the model, these recovery curves become active whenever a rider is operating below CP20, incrementally restoring a portion of FRC according to the

individual's biexponential characteristics. The mathematical formulation for the change in FRC during a small time interval is provided in Appendix C.

If the actual power output by a rider, $Power_r(t)$, remains above $CP20_r$, then no FRC reconstitution occurs; instead, FRC continues to deplete following the relevant depletion model. By iterating through consecutive time segments in which the rider remains below CP20, the model approximates how much anaerobic capacity is regained over the course of the race. Differences in $\tau_{fast,r}$, $\tau_{slow,r}$, and the associated amplitudes allow us to capture the observed variation in recovery profiles across athletes. Figure 8 details how $\Delta FRC_r(t)$ is calculated during a race.

Position-Specific Constraints

The MIP must reflect that not all riders can fill each position effectively.

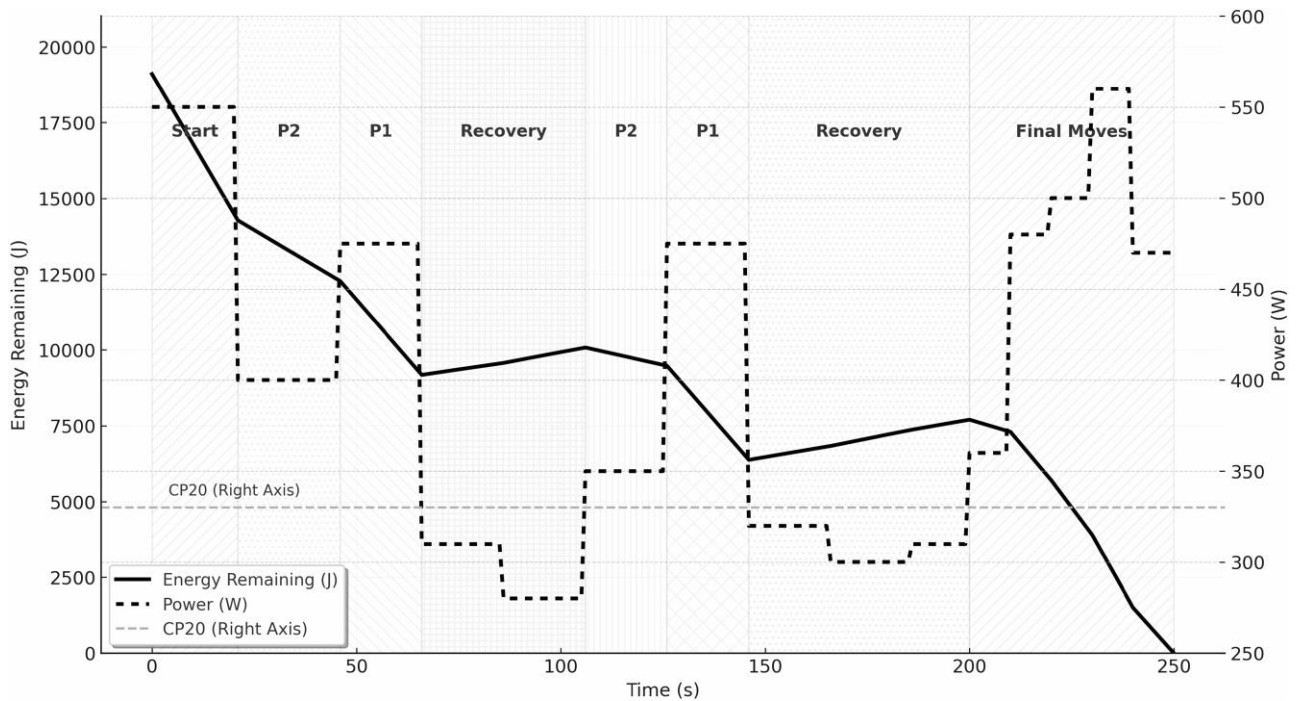
Positional Versatility. Some cyclists can handle multiple roles (e.g., strong starting pulls in P1 followed by consistent midrace efforts), whereas others struggle if asked to launch the race in P1. Constraints forbid specific riders from taking the P1 slot at the start whenever data show that they cannot cope with the associated acceleration demands.

Maintaining Rider Order. Once the race starts, the leader (P1) transitions to the back (P4) after pulling or possibly becomes the dropped rider if designated to exit the race. These transitions (e.g., $P1 \rightarrow P4$, $P2 \rightarrow P1$) must follow the standard rotation of a paceline (a line of riders who take turns leading to share the aerodynamic workload). The MIP enforces these logical handovers via constraints linking each rider's position from one segment to the next, forbidding impossible jumps such as moving from P4 directly to P1 in a single half-lap.

Drop Mechanics. If a rider enters the drop position, she cannot rejoin the rotating line. This reflects the four start, three finish nature of team pursuit, allowing the solver to determine optimal drop timing without later reintroducing the dropped cyclist.

Rotation Scheduling and Its Impact

The rotation schedule directly determines how many laps or sublaps each rider spends at the front. Riders at P1 experience full aerodynamic drag but grant those in P2, P3, and P4 partial recovery and potential FRC reconstitution. By carefully choosing each pull length and sequencing who leads at specific points, the model spreads the workload according to each cyclist's power output, aerodynamic efficiency, and recovery profile.

Figure 8. A Rider's Modeled $\Delta\text{FRC}_r(t)$ for a Team Pursuit Race Effort Starting in the P2 Position

Notes. FRC represents the finite energy reserve available for efforts above critical power. This shows how power changes per position and the associated energy drain and reconstitution, depending on race power compared with CP20 represented by the horizontal dashed line. All riders have high power and associated energy drain during the initial acceleration up to race speed.

Model Validation

After incorporating the key strategic and physiological components into the MIP framework, the final step was to verify that the model could faithfully reproduce known race results and performance patterns. To achieve this, USA Cycling tested the model on previous race scenarios in which the rider order, rotation schedule, and drop timing were already documented. By inputting each athlete's power profiles, aerodynamic parameters, and any relevant race-day track conditions, the team could compare the MIP's simulated finishing times to the real outcomes.

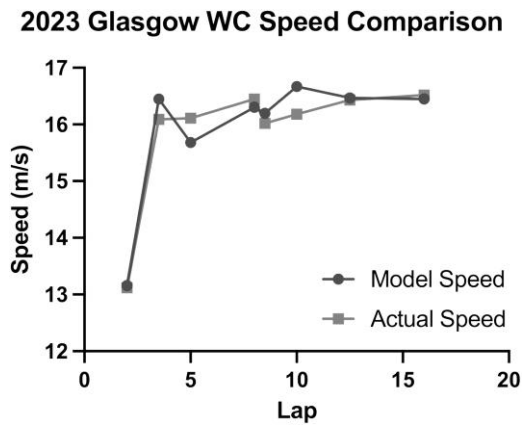
Fixed Ride Order and Pull Schedule. In these validation runs, athlete positions and lap-by-lap strategies were constrained to mirror actual decisions made in past competitions. This approach prevented the solver from optimizing the outcome, effectively turning the MIP into a predictive simulator under predetermined conditions.

Comparing Predicted vs. Actual Performance. For each event tested, the difference between the model's projected finishing time and the team's recorded finishing time was typically within 1%. Minor discrepancies typically stemmed from small variations in rolling resistance, momentary surges or slowdowns, or environmental changes that were not perfectly accounted

for in the model's assumptions. Figures 9 and 10 show the detailed speed differences and the running time delta between the model and actual performance at the 2023 World Championship in Glasgow. Investigation into the areas in which the model differed the most showed that our wind tunnel-tested drag area inputs for athletes differed slightly from our later observations in real-world testing. That said, the overall accuracy of the model provided confidence.

Building Confidence in the Model. These validation results reinforced the model's credibility as a decision support tool. Seeing the MIP reproduce past performances with a high degree of accuracy gave the USA Cycling team the confidence to rely on its outputs when designing future race strategies and setting ambitious performance goals. Figure 11 shows the time differences between the model and actual race finishing times based on the MIP model as a simulation tool. A negative time difference means that the model predicted a faster than actual time, and a positive value meant that the model predicted a slower than actual time. Earlier races (2021 through early 2023) showed greater discrepancies, but more accurate athlete monitoring in the year leading up to the Paris Games resulted in improved model accuracy. The model tended to overestimate time predictions from 2022 to early 2023, indicating that the drag area

Figure 9. Speed Differences Between the Modeled Race and Actual Race Results with a Fixed Race Strategy



Note. WC refers to World Championship.

measurements for this group of athletes may have been overly optimistic.

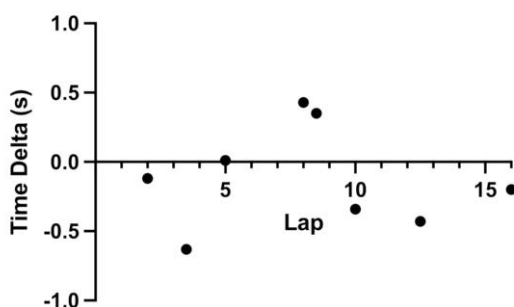
By demonstrating strong alignment between historical data and MIP-based forecasts, the project team validated the core logic of the framework. This foundation paved the way for creating specific medal-capable and gold medal-capable athlete profiles, which informed targeted training regimens, detailed rotation plans, and precise drop strategies for future high-stakes competitions such as the Paris 2024 Olympics.

Creating Baseline Athlete Profiles Through Simulation

Once the MIP framework was validated, USA Cycling used Python and Gurobi to automate a series of model runs aimed at defining the essential physiological and aerodynamic profiles required for medal- and gold-capable performances. In these simulations, the same baseline profile was applied to each of the four riders,

Figure 10. Time Difference Between Modeled and Actual Lap Times, Demonstrating That the Model Is Within 0.5 Seconds for Each Lap and 0.2 Seconds Below Actual Time for the Race

Glasgow WC Model vs. Actual Running Time Delta



Note. WC refers to World Championship.

allowing the solver to explore how varying ranges of CdA , CP_{20} , FRC , P_{Max} , and biexponential recovery rates would affect finishing times.

Leveraging historical track data from elite-level racing, the analytics team established narrow ranges for each metric (e.g., $0.16 \leq CdA \leq 0.185 \text{ m}^2$, $280 \leq CP_{20} \leq 320 \text{ W}$). These intervals represented realistic boundaries for top athletes.

A Python script iterated over these parameter combinations and ran the MIP for each scenario. Rather than forcing individualized rider profiles, the team started by assigning the same hypothetical profile (i.e., identical CdA , CP_{20} , FRC , P_{Max} , and recovery rates) to all four positions. This simplified approach quickly identified the minimal thresholds needed to achieve times near 4:07 (podium) and 4:05 (gold).

Once the solver finished, the team analyzed the finishing times across all runs. The best solutions converged on specific metric thresholds that, if met by each rider, would reliably produce finishing times near the target range.

Although exact numbers vary by athlete, Table 1 shows an example of the threshold values that emerged from these simulation runs for top three (i.e., podium-capable) versus gold-capable rider profiles. Meeting or surpassing these metrics under expected Paris conditions yielded modeled times of 4:07 and 4:05, respectively.

With these ideal profiles now established, the next step was to track and compare actual athletes to these benchmark metrics—a process we describe in the following section.

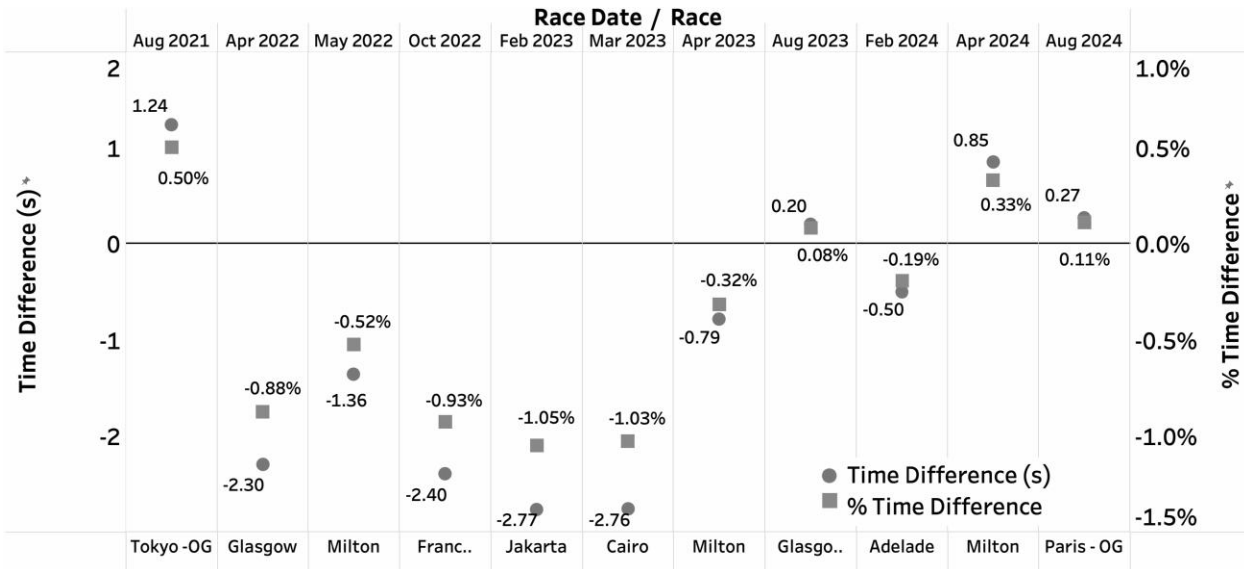
Athlete Selection and Continuous Monitoring

Identifying the required physiological benchmarks was only part of the solution. USA Cycling then turned to ongoing data tracking and real-time analysis to ensure riders were progressing toward—or exceeding—the thresholds necessary for a podium or gold medal finish.

Translating Model Output into Athlete Insights

The solver's simulation runs provided quantifiable targets for each key performance parameter, clearly indicating how close individual athletes were to achieving the metrics required for a sub-4:07 or sub-4:05 team result. For example, if a cyclist's FRC measurement fell short of the gold-standard threshold, coaches could focus on high-intensity interval training to expand anaerobic capacity. Similarly, if a rider's drag area was too high, targeted aerodynamic refinements such as new helmets, optimized positioning, or an alternative skinsuit design could help that rider move closer to the MIP's projected optimal state. Our athletes' physiological metrics were continuously calculated from data

Figure 11. Historical Race Time and Percentage Differences of Model Time vs. Actual for 11 Elite-Level Competitions from the Tokyo Olympics 2021 Through the Paris Olympics 2024



gathered during each training ride, race performance, and laboratory test, and these metrics were monitored via our athlete dashboard. Additionally, aerodynamic data validated through track training sessions and equipment dress rehearsals were used to further inform coaching decisions.

Data Tracking and Z-Scores

To manage the wealth of real-time data coming from power meters, aerodynamic sensors, and laboratory tests, USA Cycling utilized standardized industry tools and software (e.g., TrainingPeaks and WKO, which are commercial platforms for tracking and analyzing cycling performance data) alongside a Z-score system (a statistical measure showing how many standard deviations a value is from the mean). Each performance metric was measured and standardized against the gold-capable reference profile:

$$Z_{\text{athlete } i} = \frac{\text{Metric}_i - \mu_{\text{gold-capable}}}{\sigma_{\text{gold-capable}}}$$

where $\mu_{\text{gold-capable}}$ and $\sigma_{\text{gold-capable}}$ represent the distribution of values used in the MIP simulation. By adopting Z-scores, the team could rapidly see which

athletes were consistently above or below the ideal range. A rider posting positive Z-scores across multiple parameters (e.g., FRC, CP20, low drag area) signaled an individual who might be ready for a leading role in P1 or P2.

Conversely, negative Z-scores revealed performance gaps (e.g., an insufficient aerobic base or suboptimal aerodynamics). This insight enabled coaches to tailor training programs to address specific weaknesses whether that meant focusing on threshold power, improving riding position, or enhancing top-end anaerobic development. Table 2 presents a pre-training camp Z-score snapshot, taken several months before the Olympics, that helped identify focus areas for each rider. Notably, large negative values in FRC were often associated with early season injuries that limited high-intensity interval training.

Team Selection

Although the model output provided a data-driven foundation, in the weeks leading up to the Olympic Games, coaches and performance staff also weighed intangible factors such as a rider’s consistency under pressure, past team dynamics, or injuries. By combining these subjective evaluations with the MIP-based results, they arrived at a final four athlete team roster with an additional alternative. Once selected and approved by the selection committee, based on the data provided, these riders underwent a final training block designed to maximize alignment with the solver’s recommended rotation schedules and pacing strategies.

Equipment Testing and Skinsuits

At speeds above 60 km/h (40 mph), aerodynamic drag overwhelmingly dominates the forces acting on

Table 1. Example Output from the MIP Simulation

Focus area	Top three	Gold
CdA (m ²)	<0.170	<0.168
FRC (kilojoules)	>17.5	>18.0
CP20 (watts)	>305	>310
P _{Max} (watts)	>1,050	>1,100

Note. Each rider meeting or exceeding these thresholds made a 4:07 or 4:05 finishing time highly feasible.

Table 2. Z-Score Tracking Data for Athletes

Athlete	Z_CP20	Z_FRC	Z_Drag Area	Z_PMax	Total Z	Selected
Athlete 1	0.58	-2.11	0.00	0.09	-1.44	✓
Athlete 2	0.07	0.89	-1.20	3.64	3.40	✓
Athlete 3	-1.35	0.67	-0.30	-1.44	-2.42	✓
Athlete 4	1.42	1.33	0.00	-1.67	0.08	✓
Athlete 5	-2.13	-8.56	0.10	0.09	-10.50	✓
Athlete 6	-3.23	-3.56	-0.40	0.85	-6.34	
Athlete 7	-1.23	-4.89	-0.70	-0.35	-6.17	

Note. Athlete 5 was selected despite her negative total Z because she possessed the P_{Max} and skills necessary to serve as backup P1 starter.

a team pursuit squad. In search of marginal gains, USA Cycling collaborated closely with Vorteq Sports (a company specializing in aerodynamic analysis and optimization for cycling) to push the limits of aerodynamic efficiency. The partnership began by generating a 3D body scan of each athlete who had potential to make the team. These scans provided precise digital models of each individual’s physique and posture on the bike, forming the basis for 19 custom skinsuits, each featuring unique patterns, layering techniques, and textiles designed for different athlete body types, riding positions, and race scenarios. As we show in Table 3, this helped drive a 9.2% reduction in CdA .

To streamline the development process, two athletes were selected for the creation of 3D mannequins, allowing ongoing experiments in the wind tunnel even when the riders were unavailable as shown in Figure 12. This capability significantly accelerated the design and iteration of new skinsuit prototypes. Each iteration underwent controlled wind-tunnel sessions to measure CdA and closely examine how modifications in suit construction, seam placement, or fabric choice influenced airflow around the rider’s body.

Crucially, aerodynamic gains observed in the wind tunnel needed to translate effectively to the velodrome. To confirm real-world applicability, the team deployed advanced wind-speed sensors and power meters during routine training sessions. These instruments enabled real-time calculations of drag area for each rider, ensuring that athletes could consistently maintain compact and efficient positions without compromising power output. Data gathered from these in situ sessions frequently prompted additional suit adjustments—sometimes involving fit, fabric

tension, or even posture cues—resulting in iterative improvements that aligned laboratory-based theories with actual performance on the track.

Implementation Journey and Challenges

Although the MIP and aerodynamic innovations provided a strong analytical foundation, converting these insights into an actual gold medal performance demanded comprehensive buy-in and seamless coordination. From the project’s inception, USA Cycling’s analytics team partnered closely with high-performance coaches, the U.S. Olympic & Paralympic Committee (USOPC) data team, and the athletes. This ensured that each step, from early goal setting through final race-day strategy and execution, was both data driven and pragmatically tested.

Building Trust with Coaches and Athletes

Fostering genuine confidence among coaches and riders was crucial. The analytics staff organized periodic

Figure 12. The Use of 3D Mannequins in Wind-Tunnel Testing Skinsuit Designs Reduced Development Time and Prevented Athletes from Losing Precious Training Time

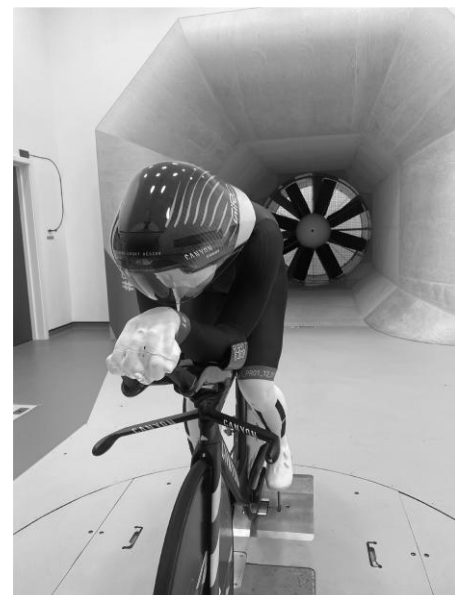


Table 3. Drag Area Reductions Across a Range of Prototype Skinsuits

Prototype	Measured CdA (m ²)	Reduction versus baseline, %
Baseline suit	0.185	—
Prototype 5	0.179	3.2
Prototype 3	0.176	4.9
Prototype 19	0.168	9.2

sessions to explain why specific rotation plans or equipment upgrades emerged from the model's results, and coaches set up pilot runs at training camps to compare MIP predictions against real-world outcomes. When the data consistently mirrored actual performances, both historically (as shown in Figure 11) and in controlled tests, initial skepticism gave way to growing optimism.

That optimism transformed into tangible confidence when the team reviewed a model-generated scenario from the team's 2023 Glasgow World Championships data. By altering the race pull structure and pacing strategy, the MIP indicated a possible time of 4:08.64 given that day's track conditions. This was 0.131 seconds faster than Great Britain's gold medal time of 4:08.771 at that event. For elite athletes familiar with razor-thin margins, this numerical "what if" underscored the potential of the modeling approach to achieve medal-producing gains.

A key part of the trust-building process involved sharing individual athlete and combined team Z-scores. The analytics team and coaching staff met with each rider to highlight specific strengths (e.g., a high CP20 or exceptionally low drag area) and recommend targeted training adaptations for areas of deficiency (e.g., boosting FRC via high-intensity efforts). By directly linking these tailored improvements to the unified objective of breaking the 4:05 barrier, the coaches not only underscored the importance of each individual's progress but also sparked a collective belief that each rider's effort was vital to the team's overall success.

Athlete Injuries

During the project, we also faced unexpected issues with athlete injuries. Cycling as a sport has an inherent risk of injury because of crashes. At the speeds at which these athletes race, crashes can have devastating and even deadly consequences. In the lead-up to the Olympic Games, three of the four riders on the team faced significant injuries, limiting their training progression. Going into the competition, two athletes' physical power metrics lagged their own benchmarks from the 2023 World Championship.

Although these circumstances were certainly worrisome, the model's continued demonstration of potential record-breaking times despite the setbacks gave everyone involved a level of confidence in the days before the race. Even with limited training volumes, the MIP's rotation strategies and pacing optimizations indicated that the team could still remain a strong medal contender. These results showcasing the team's capacity to compensate for individual shortfalls helped sustain morale and propelled the riders through to race day.

On-Track Validation

Once the riders returned to near-full capacity, the final training camp before the Olympics offered the perfect

setting to refine the MIP-recommended rotation patterns. Power meter data from these sessions consistently verified significant time savings over the more improvised methods that had been used before.

A pivotal moment occurred when the coaches had to persuade one of the team's most decorated and strongest riders—a multiple-time individual Olympic and World Championship gold medalist—that her optimal contribution would involve starting in the P1 position and dropping out of the race after her second extended pull. Intentionally removing one of the team's strongest riders is virtually unheard of and was an action that had never been taken in team pursuit, especially not at the Olympic level. Typically, weaker riders are forced to drop because of fatigue and an inability to hold the desired speed and power. However, according to the MIP, this rider's preplanned midrace exit, coupled with shorter initial pulls from the other riders, would prevent the team's speed from plummeting in the final kilometers, thereby maximizing the overall pace for the remaining trio. Initially skeptical, the time splits and power curves supported the idea that a relatively early departure would prevent a late-race collapse. Real-world tests in training validated the theory.

Overcoming Funding and Resource Constraints

Although top-funded federations enjoyed virtually unlimited access to elite-level competition in Europe, wind-tunnel time, and high-performance staff, USA Cycling operated with a significantly more constrained budget. Primarily financed by the USOPC, private donations, and sponsorships, USA Cycling's budget is directly tied to its ability to win Olympic medals (Novy-Williams and Akabas 2024). Direct budget comparisons based on USOPC financial statements show that USA Cycling received an average of \$2.8 million annually compared with Great Britain's \$12 million and Australia's more than \$8 million (U.S. Olympic & Paralympic Committee 2023, 2024; Farrand 2024; Australian Institute of Sport n.d.).

The analytics team helped address these constraints by targeting areas that, according to our data analyses, offered the highest potential returns. One such focus was optimizing aerodynamically efficient skinsuits (colloquially called slippery suits) for riders with elevated drag area, thereby maximizing the impact of each wind-tunnel session.

Moreover, close collaboration among coaches, sports scientists, and data analysts minimized duplicative efforts across the organization. By strategically aligning training camps, laboratory tests, and wind-tunnel sessions, USA Cycling streamlined its limited resources to maximize performance gains. Consequently, this data-driven approach served as a force multiplier, effectively

bridging the budget gap between the United States and more highly funded teams.

The Ultimate Parisian Model Validation

In the weeks leading up to the event, the analytics team and coaches closely tracked each athlete's real-time metrics and validated the MIP solutions against daily changes in track conditions. Air density—one of the most critical inputs—was monitored for potential deviations from the expected 1.14 kg/m^3 . Any fluctuation, however small, could slightly alter rotation or pull timing.

By this stage, everyone understood that a sub-4:05 ride was possible in principle, yet this team of four riders had never completed a team pursuit faster than 4:11 in an official race. Because the event is so taxing, only specific race segments and scenarios are practiced in training sessions, leaving some uncertainty about whether the model's projected gains would fully translate to the competition.

Qualifying Round: Setting the Tone

In the women's team pursuit, the first ride is a solo qualifying round, in which teams race against the clock to determine subsequent matchups. On race day, the measured air density hovered at 1.142 kg/m^3 , prompting a final run of the MIP. The result confirmed our bold plan. Jennifer Valente, a two-time Olympic medalist at the time, would perform a long pull from the start for 2.5 laps—the longest rotation of any U.S. rider. After one complete rotation cycle, in which riders executed relatively short pulls to limit the time spent exerting full power at the front (5.5 laps later), she would return to the front for another monumental two-lap effort. She pushed herself to the limit before dropping out halfway through the race. This strategy allowed riders with lower FRC values to spend more time early in the race reconstituting energy after a blistering 21.7-second start lap, enabling them to be fresher during the second half of the race.

Executing this plan yielded a stunning 4:05.20—a new U.S. record that nearly met the 4:05 threshold set months earlier. The team and coaches now knew that breaking the 4:05 barrier was within reach in a competitive setting. Having qualified with the second fastest time overall—with only the favorite, New Zealand, posting a faster split at 4:04.679—Team USA was set to face the third seeded and second highest ranked Great Britain squad in the next round.

Round 2: Facing the Second Best Team

Historically, Great Britain has dominated elite-level track cycling, securing eight gold medals across all women's Olympic track events compared with Team USA's one medal leading up to the Paris Games.

British Cycling also boasts the highest reported budget of any Olympic cycling program—more than double that of USA Cycling when combining all sources of funds (USA Cycling Inc. 2024). Moreover, it pioneered the concept of marginal gains in cycling, in which each aspect of performance is meticulously planned by teams of experts from nutritionists to aerodynamicists and in-house data scientists (Kirkland et al. 2013). If any team could match our aerodynamic efficiencies and optimal pull strategy, British Cycling would be that team.

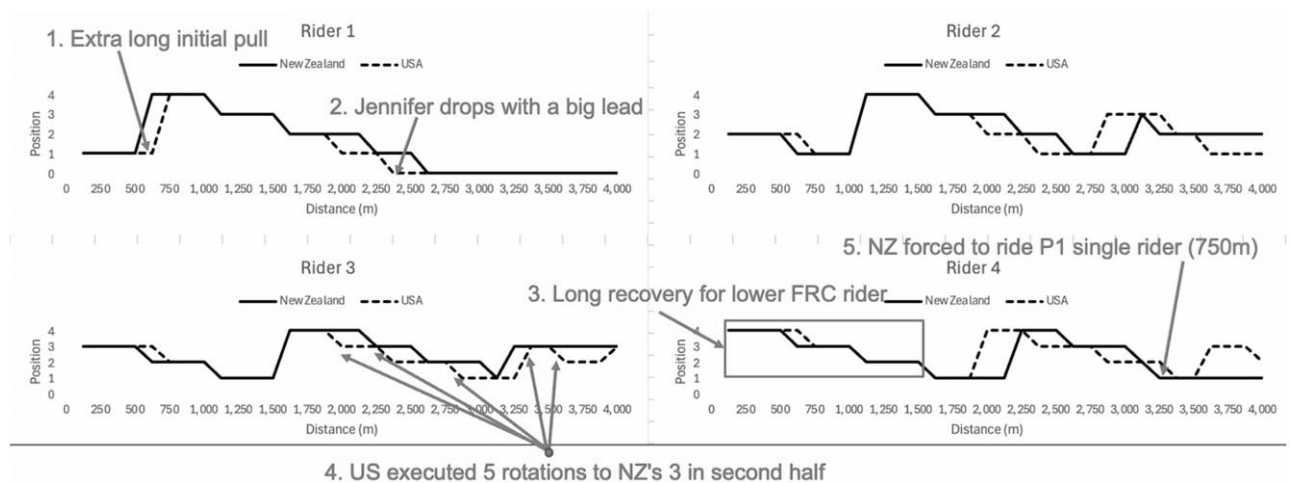
In head-to-head team pursuit races, having a second team on the track sometimes creates a swirl effect, creating something analogous to a tailwind when the competitors are evenly matched. Running the model again with a small adjustment to airspeed to account for this phenomenon predicted an even faster time, around 4:04.8, for the same pull strategy.

Adhering to the same rotation order—and, crucially, retaining the plan for Jennifer's midrace drop—the U.S. squad posted a time of 4:04.629, faster than both the qualifying round and the predicted time. Most importantly, it was slightly faster than Great Britain's time of 4:04.908. This result not only generated the best time thus far in the competition but also guaranteed Team USA a spot in the gold medal round. Breaking the 4:05 mark in an official race was a major psychological boost; the team had proven it could not only meet but also surpass its ambitious model targets.

Gold Medal Round: Racing the Favorite, New Zealand

In the final showdown, Team USA faced a formidable New Zealand squad that was ranked number one in the world going into the Olympics and having posted the fastest qualifying time (4:04.679 compared with Team USA's 4:05.20). Confident in its preparation, Team USA lined up for the finals as if victory were a foregone conclusion. The model predicted a time of 4:04.45, and the team had consistently outperformed this benchmark. Although it would take a monumental effort from New Zealand to match this performance, the race is never won on paper or in code.

Other U.S. athletes and staff gathered in the velodrome, anticipating a close contest. The team maintained the same rider order, drop strategy, and overall pull schedule as previous rounds. At the halfway point, everything was on track: Team USA led New Zealand by 1.27 seconds as Jennifer Valente completed her final pull. Although the race appeared to be in hand, the cumulative fatigue from multiple days of racing began to show in the final laps. Riders 3 and 4 started to lose contact with the lead rider (Chloé Dygert), who was on pace for a new world record. In the final lap, the early race strategy that had built a

Figure 13. Differences in Pull Strategies Between USA and New Zealand by Rider

substantial U.S. lead became challenging to sustain, but New Zealand's third rider also began to fatigue and fall behind. Ultimately, Team USA bested the model's prediction by 0.2 seconds and further improved upon its previous best result and national record, stopping the clock at 4:04.306—enough to beat New Zealand's time of 4:04.92 for the victory.

Figure 13 illustrates the differences in pull strategies between Team USA and the New Zealand team during the race. Although the strategies may appear similar at first glance, when dealing in fractions of a second, every detail matters. Team USA executed two additional rotations (nine compared with New Zealand's seven), providing an extra 30 seconds of recovery time and reduced pull time for fatigued riders. Additionally, the order of riders was paramount. Having Jennifer lead out the first half of the race from P1—when she maintained an average power output of more than 620 watts (a measure of power in which one watt equals one joule per second) and reached peak power levels exceeding 1,100 watts—was key to establishing a fast start and conserving energy for riders with lower *FRC* values. In contrast, New Zealand's equivalent rider, Ally Wollaston—who later won bronze to Jennifer's gold in the women's omnium event—started in P4, requiring her to perform the majority of the team's work during the final quarter of the race, in which she spent the last 750 meters in the lead position. New Zealand's strategy more closely resembled the pull structure that Team USA used at the 2023 Glasgow World Championships, in which the rider order was different and the team was forced to sustain much longer pull durations at the end of the race.

The winning time marked a remarkable leap forward from the 4:12 recorded at the 2023 World Championships, illustrating that strategic analytics and targeted resource allocation can rival—and even surpass—federations with significantly larger budgets. The consistent

improvements observed in each round affirmed the accuracy of our MIP optimization strategies and predicted times. Although it is the riders who put in the hard training hours, ride with purpose, and win medals, this success underscores the unwavering commitment of the coaches, staff, and athletes who trusted our analytics process and optimization modeling. They executed the team's vision and achieved greatness: a gold medal.

Conclusion

Project 4:05 illustrates how operations research (OR), data analytics, simulation, real-time performance tracking, meticulous testing, and aerodynamic innovation can drive transformative change in an Olympic setting:

- Innovative use of data analytics methodologies: By integrating goal-time prediction models, our MIP framework, and real-time athlete monitoring tools, USA Cycling introduced a novel, multiphase approach to optimizing complex tactical decisions—such as athlete selection, rider order, rotation schedules, and drop timing—based on real-time athlete data tracking and shifting environmental conditions.

- Quantifiable and significant impact: The initiative propelled the women's team pursuit from a sixth place finish at the 2023 World Championships and an eighth place world ranking to winning a gold medal at the 2024 Olympics. The project shaved critical seconds off the team's time—improving from 4:12 to 4:04.306—demonstrating a clear, measurable return on investment in analytics. Furthermore, in the world of Olympic sports, budgets are closely tied to medal counts, especially gold. At the Tokyo Olympics, USA Cycling earned only three medals. However, with a renewed focus on tactical high performance and data analytics across disciplines, the team earned six medals in Paris, including three gold—our best result to date—matching the overall gold medal

performance of USA Gymnastics. Project 4:05 also opened opportunities for new sponsorships, additional USOPC funding, and increased donations.

- **Effective implementation and real-world validation:** The sophisticated modeling approach was supported by extensive field validation—pilot runs, wind-tunnel testing, and continuous Z-score tracking—which established credibility among coaches and riders. This transparent, iterative collaboration ensured that coaches and athletes trusted and adopted model outputs even when results seemed counterintuitive.

- **Overcoming resource constraints and complexity:** Despite operating on a fraction of the budget of top-funded international programs, USA Cycling's data-driven prioritization (guided by the MIP-based optimization model and simulation framework) maximized the impact of limited wind-tunnel time and athlete training sessions. This efficient allocation of resources underscores how OR can deliver high-value outcomes under tight constraints.

- **Replication and future potential:** Beyond the 2024 Olympics, the Project 4:05 framework is being expanded to other cycling disciplines and broader USOPC initiatives, demonstrating its strong replicability. The optimization approach could benefit team sports such as rowing (crew selection and seat positioning), relay events in track and field (runner order and exchange timing), and swimming relays (stroke order and split strategies). In each case, the framework optimizes athlete selection, positioning, and tactical decisions based on individual performance metrics and team dynamics. By combining advanced analytics with domain expertise and agile implementation, the project sets the stage for continued innovation in elite sports and promises to support a record medal count at the 2028 Olympic Games in Los Angeles.

In summary, Project 4:05 embodies the core principles of impactful OR: a rigorously developed model, human-centric implementation, and demonstrable results. This remarkable transformation—from a disappointing sixth place finish to Olympic gold—demonstrates the power of data-driven decision making in elite sports. Our tactical optimization model, comprehensive data analytics, and continuous athlete performance monitoring were paramount to achieving success. More than just winning a gold medal, Project 4:05 serves as a blueprint for how OR can level the playing field against better funded competitors and foster a broader culture of analytics-driven excellence in sports.

Appendix A. Team Pursuit Optimization Model

A.1. Sets and Indices

- \mathcal{R} : Set of riders, indexed by r .

- \mathcal{P} : Set of positions, indexed by p . For the team pursuit, we have

$$\mathcal{P} := \{P1, P2, P3, P4, DP\}.$$

- $\mathcal{P}^{\text{drop}} := \{DP\} \subset \mathcal{P}$: Subset of positions containing the drop position.
- $\mathcal{P}^{\text{nondrop}} := \{P1, P2, P3, P4\} \subset \mathcal{P}$: Subset of nondrop positions.
- $\mathcal{P}^{\text{required}} := \{P1, P2, P3\} \subset \mathcal{P}$: Subset of positions that must always be filled.
- \mathcal{S} : Discrete set of possible speeds in 0.1 m/s increments, indexed by s .
- $\mathcal{L} = \{l_1, l_2, \dots, l_{31}\}$: Set of lap segments (half lap or quarter lap), indexed by l .
 - $\mathcal{L}^{\text{quarter}} := \{l_1, l_{31}\} \subset \mathcal{L}$: Subset of laps that are a quarter-lap (e.g., the start/end segments).
 - $\mathcal{L}^{\text{half}} := \{l_2, l_3, \dots, l_{30}\} \subset \mathcal{L}$: Subset of laps that are a half-lap.

A.2. Parameters

- Physical constants:

$$\begin{aligned} \rho &: \text{Air density,} \\ c_{rr} &: \text{Rolling resistance,} \\ g &: \text{Acceleration of gravity,} \\ \eta &: \text{Drivetrain efficiency,} \\ m_{\text{bike}} &: \text{Mass of the bike.} \end{aligned}$$

- Rider-specific data (for each $r \in \mathcal{R}$):

$$\begin{aligned} m_r &: \text{Mass of the rider,} \\ CdA_r &: \text{Coefficient of drag,} \\ CP20_r &: \text{Critical Power,} \\ AP_r &: \text{Acceleration Power (PMax),} \\ FRC_r &: \text{Functional Reserve Capacity.} \end{aligned}$$

- Position-specific drag modifiers:

$$CdAPos_p \quad \forall p \in \mathcal{P}^{\text{nondrop}}.$$

- Distances and times:

$$\begin{aligned} \frac{d_1}{2} &: \text{Distance of half-lap,} \\ \frac{d_1}{4} &: \text{Distance of quarter-lap,} \\ \text{speed}_s &: \text{Speed} \quad \forall s \in \mathcal{S}, \\ t_1(s) &:= \frac{\frac{d_1}{2}}{\text{speed}_s} : \text{Time to cover half-lap distance} \\ &\quad \text{at speeds} \quad \forall s \in \mathcal{S}, \\ t_1(s) &:= \frac{\frac{d_1}{4}}{\text{speed}_s} : \text{Time to cover quarter-lap distance} \\ &\quad \text{at speeds} \quad \forall s \in \mathcal{S}. \end{aligned}$$

- Energy model parameters (for each $r \in \mathcal{R}$):

$$\begin{aligned} FCamp_r, SCamp_r &: \text{Fast/slow reconstitution fractions,} \\ \text{tauFC}_r, \text{tauSC}_r &: \text{Fast/slow reconstitution time} \\ &\quad \text{constants,} \\ \text{StartTime} &: \text{Time used to compute initial} \\ &\quad \text{FRC depletion.} \end{aligned}$$

• Penalties (defined as parameters to avoid hard-coded values in the math program):

- $\alpha_{\text{switch}} \in \mathbb{R}^+$: Time impact of rotating positions,
- $\alpha_{\text{eRes}} \in \mathbb{R}^+$: High penalty cost of excess energy reserve use (typically set to 1,000 or higher to heavily discourage infeasible solutions that would require riders to exceed their physiological capacity).

A.3. Preprocessing: Power and Energy Use

A.3.1. Power Demand. For each rider r , position p , and speed s , we define power demand as

$$\text{power}_{r,p,s} = \frac{(\text{CdA}_r \cdot \text{CdA}_{\text{Pos}_p} \cdot \rho \cdot (\text{speed}_s)^3 / 2) + (c_{\text{rr}} \cdot g \cdot (m_r + m_{\text{bike}}) \cdot \text{speed}_s)}{\eta}$$

A.3.2. Energy Usage in a Half Lap. Let $\text{energyUse}_{r,p,s}$ represent the net energy cost (or gain if negative) to complete one half lap:

$$\text{energyUse}_{r,p,s} = \begin{cases} (\text{power}_{r,p,s} - \text{CP20}_r) t_1(s), & \text{if } \text{power}_{r,p,s} > \text{CP20}_r, \\ \text{reconst}_{r,p,s} \cdot t_1(s), & \text{if } \text{power}_{r,p,s} \leq \text{CP20}_r. \end{cases}$$

If $\text{power}_{r,p,s} \leq \text{CP20}_r$,

$$\alpha_{r,p,s} = \frac{\text{CP20}_r - \text{power}_{r,p,s}}{\text{CP20}_r}, \quad \text{tauFC}_{r,p,s}^{\text{adj}} = \frac{\text{tauFC}_r}{1 + \alpha_{r,p,s}},$$

$$\text{tauSC}_{r,p,s}^{\text{adj}} = \frac{\text{tauSC}_r}{1 + \alpha_{r,p,s}},$$

$$\text{reconst}_{r,p,s} = -[(\text{AP}_r - \text{CP20}_r) \text{StartTime} (\text{FCamp} (1 - e^{-1/\text{tauFC}_{r,p,s}^{\text{adj}}}) + \text{SCamp} (1 - e^{-1/\text{tauSC}_{r,p,s}^{\text{adj}}}))].$$

A similar definition applies for quarter laps, using $t_{\frac{1}{4}}(s)$ instead of $t_{\frac{1}{2}}(s)$.

A.3.3. Initial FRC and Total Capacity. Each rider r has an adjusted starting capacity:

$$\text{startingFRC}_r = \text{FRC}_r \times 1,000 - (\text{AP}_r - \text{CP20}_r) \text{StartTime},$$

and the total capacity

$$\text{totalJoules}_r = \text{FRC}_r \times 1,000.$$

A.4. Decision Variables

The main decision variables in the math program are the following:

- $x_{r,p,s,l} \in \{0,1\}$: one if rider r is in position p at speed s during segment l .
- $\text{isInDP}_{r,l} \in \{0,1\}$: one if rider r is in the DP in lap l .
- $\text{lapSpeed}_{l,s} \in \{0,1\}$: one if segment l uses speed s .

We also have the following variables in the math programming formulation.

- $\text{switchRider}_{r,l} \in \{0,1\}$: one if rider r switches from lap l to $l+1$.
- $\text{emergencyReserves}_r \in \mathbb{R}^+$: emergency energy reserve for rider r used to prevent infeasibility.

A.5. Objective Function

We minimize total time plus penalties:

$$\begin{aligned} \min \text{StartTime} &+ \frac{1}{|\mathcal{R}|} \sum_{r \in \mathcal{R}} \sum_{p \in \mathcal{P}} \sum_{s \in \mathcal{S}} \left(\sum_{l \in \mathcal{L}^{\text{half}}} \frac{t_1(s)}{2} x_{r,p,s,l} + \sum_{l \in \mathcal{L}^{\text{quarter}}} \frac{t_1(s)}{4} x_{r,p,s,l} \right) \\ &+ \sum_{r \in \mathcal{R}} \sum_{l \in \mathcal{L}} \alpha_{\text{switch}} \text{switchRider}_{r,l} + \sum_{r \in \mathcal{R}} \alpha_{\text{eRes}} \text{emergencyReserves}_r. \end{aligned}$$

Note that we assume all riders to have the same speed, including the dropped rider with no energy degradation. Hence, we divide the total time taken by all the riders by a factor equal to the total number of riders (four in a team pursuit race) to calculate the average time and, thus, the overall finishing time in the objective.

A.6. Constraints

i. One position per rider per lap:

$$\sum_{p \in \mathcal{P}} \sum_{s \in \mathcal{S}} x_{r,p,s,l} = 1, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

ii. Positions that must be filled:

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} x_{r,p,s,l} = 1, \quad \forall p \in \mathcal{P}^{\text{required}}, l \in \mathcal{L}.$$

iii. At most one rider per position per lap:

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} x_{r,p,s,l} \leq 1, \quad \forall p \in \mathcal{P} \setminus \mathcal{P}^{\text{required}}, l \in \mathcal{L}.$$

iv. Linking $\text{isInDP}_{r,l}$:

$$\text{isInDP}_{r,l} = \sum_{s \in \mathcal{S}} x_{r,\text{DP},s,l}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

v. No nondrop positions after DP:

$$\sum_{p \in \mathcal{P}^{\text{nondrop}}} \sum_{s \in \mathcal{S}} \sum_{l \in \mathcal{L}: l > l} x_{r,p,s,l} \leq 1 - \text{isInDP}_{r,l}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

vi. Energy limit (total FRC):

$$\sum_{p \in \mathcal{P}^{\text{nondrop}}} \sum_{s \in \mathcal{S}} \sum_{l \in \mathcal{L}} \text{energyUse}_{r,p,s} x_{r,p,s,l} \leq \text{startingFRC}_r + \text{emergencyReserves}_r, \quad \forall r \in \mathcal{R}.$$

vii. Strictly no negative FRC before end:

$$\text{startingFRC}_r - \sum_{p \in \mathcal{P}^{\text{nondrop}}} \sum_{s \in \mathcal{S}} \sum_{l \in \mathcal{L}: l < l} \text{energyUse}_{r,p,s} x_{r,p,s,l} \geq 0, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

viii. Uniform speed per lap:

$$\sum_{s \in \mathcal{S}} \text{lapSpeed}_{l,s} = 1, \quad \forall l \in \mathcal{L}.$$

ix. Link rider speed to lap speed:

$$\sum_{r \in \mathcal{R}} \sum_{p \in \mathcal{P}} x_{r,p,s,l} = |\mathcal{R}| \text{lapSpeed}_{l,s}, \quad \forall l \in \mathcal{L}, s \in \mathcal{S}.$$

x. Switch constraints (generalized):

$$\text{switchRider}_{r,l} \geq \sum_s x_{r,p,s,l} - \sum_s x_{r,p,s,l+1}, \quad \forall r \in \mathcal{R}, p \in \mathcal{P}, l \in \mathcal{L}.$$

For example, if a rider switches out of P1 after lap segment l , the right-hand side takes a value of one. Note that any rider r is always in a position $p \in \mathcal{P}$ (per Equation (B.1)), and thus, any switch ensures that $\text{switchRider}_{r,l}$ takes a value of one.

xi. Position succession (P1):

$$\sum_s x_{r,P1,s,l} = \sum_s x_{r,P4,s,l+1} + \sum_s x_{r,P3,s,l+1} + \sum_s x_{r,P1,s,l+1} + \sum_s x_{r,DP,s,l+1}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

From P1, a rider has the following possible transitions: P1 → P4 (standard rotation), P1 → DP (if designated to drop), stay P1 (if holding position), or P1 → P3 (only possible after another rider has dropped because this constraint combined with constraint (ii) (i.e., positions that must be filled) prevents the P1 rider from moving to P4 once a drop has occurred).

xii. Position succession (P2):

$$\sum_s x_{r,P2,s,l} = \sum_s x_{r,P1,s,l+1} + \sum_s x_{r,P2,s,l+1}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

From P2, a rider has the following possible transitions P2 → P1 or stay P2.

xiii. Position succession (P3):

$$\sum_s x_{r,P3,s,l} = \sum_s x_{r,P2,s,l+1} + \sum_s x_{r,P3,s,l+1}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

From P3, a rider has the following possible transitions P3 → P2 or stay P3.

xiv. Position succession (P4):

$$\sum_s x_{r,P4,s,l} = \sum_s x_{r,P3,s,l+1} + \sum_s x_{r,P4,s,l+1}, \quad \forall r \in \mathcal{R}, l \in \mathcal{L}.$$

From P4, a rider has the following possible transitions P4 → P3 or stay P4.

Appendix B. Drag and Power Equations

The aerodynamic forces acting on cyclists are described by the following fundamental equations.

The drag force acting on a cyclist is given by

$$F_d = \frac{1}{2} \rho v^2 C_d A, \quad (B.1)$$

where F_d is the drag force (N), ρ is the air density (kg/m³), v is the velocity (m/s), C_d is the drag coefficient, and A is the frontal area (m²). The power required to overcome air resistance at a given velocity is

$$P = \frac{1}{2} \rho v^3 C_d A. \quad (B.2)$$

The drag coefficient and frontal area are often combined into a single parameter called drag area:

$$C_d A = \text{drag coefficient} \times \text{frontal area}. \quad (B.3)$$

Power in cycling is typically measured in watts (W), where 1 watt = 1 joule/second.

Appendix C. FRC Reconstitution Equation

One possible formulation for the change in FRC during a small time interval Δt (e.g., a half-lap segment) is

$$\Delta \text{FRC}_r(t) = \left[\text{FCamp}_r \left(1 - e^{-\frac{\Delta t}{\tau_{\text{fast},r}}} \right) + \text{SCamp}_r \left(1 - e^{-\frac{\Delta t}{\tau_{\text{slow},r}}} \right) \right] \times \max(0, \text{CP20}_r - \text{Power}_r(t)) \times \Delta t, \quad (C.1)$$

where

- $\text{FRC}_r(t)$ is the rider's current FRC state at time t .

- FCamp_r and SCamp_r are fractional amplitudes that partition the total recovery between the fast and slow components.

- $\tau_{\text{fast},r}$ and $\tau_{\text{slow},r}$ are time constants (in seconds) for the fast and slow recovery processes.

- CP20_r is the rider's critical power (the approximate threshold below which anaerobic reserves can begin to recover).

- $\text{Power}_r(t)$ is the actual power output by the rider at time t .
- Δt is the duration of the segment (e.g., a quarter-lap).

Appendix D. Air Density Normalization Equation

The following equation describes the normalization of finishing times to account for different air density conditions:

$$T_{\text{normalized}} = T_{\text{raw}} \left(\frac{\rho_{\text{measured}}}{\rho_{\text{baseline}}} \right)^{\frac{1}{3}},$$

where

- T_{raw} is the measured finish time at air density ρ_{measured} .
- $T_{\text{normalized}}$ is the time adjusted to the baseline air density ρ_{baseline} (e.g., 1.14 kg/m³ for the Paris velodrome).
- The exponent $\frac{1}{3}$ reflects the approximate velocity–drag–power relationship in cycling.

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