# Cooperation in Bike Racing—When to Work Together and When to Go It Alone

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*We present an agent-based model of bicycle racing that incorporates both physiology and the types of multiplayer scenarios that arise in real races. In these scenarios, riders can choose to share the workload with other riders (cooperate) or pursue their own self-interests (defect). We compare the model's predictions to race situations and use it to investigate how different strategies can affect outcomes. We find that an individual player's best strategy depends on fitness level: below-average riders fare better as defectors whereas above-average riders perform better as cooperators. The strategies of stronger riders affect their teammates' results as well. The teammates of defecting strong riders fare worse overall than the teammates of cooperating strong riders. These results reproduce a dynamic that played out in the 2009 Tour de France. The winner, Alberto Contador, pursued a strategy perceived by many to be unusually uncooperative by repeatedly defecting on his teammates. The strategy worked to his advantage but may have negatively affected his teammates' placements.*  *Complexity 17: 39–44, 2011*

**Key Words:** agent-based model; bike racing; agent-based simulation; cooperation

## 1. INTRODUCTION

To the casual observer, the sport of bike racing might appear to be a purely individualistic sport, where lone cyclists ride as fast as possible to a finish line. In most bike races, however, individuals are members of a team that employs complex strategies including cooperation and defection. In these races, air resistance dominates energy expenditures, so riders from different teams often form temporary cooperative alliances, rotating one by one into the lead position of the group and allowing others to "draft" in their slipstream. Those in the slipstream expend 30–40% less energy [1–3] than they would in the lead position going the same speed. Members of such a group can defect by "sitting in"—not taking their turn, or a long enough turn, at the front, and thereby conserving energy to sprint ahead at a critical point later in the race. Riders in these groups are alert to this possibility and continually monitor one another; if defection is perceived, others in the group often take action, by increasing the pace to "drop" the defector, for instance. Defection can also take the form of an explosive sprint off the front of the group, often when the defector has observed that other riders are tired.

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For all of these reasons, an individual's decision about whether or not to cooperate with a given group of riders is extremely complicated, and results of different decisions are difficult to model. A group of riders that work well together, taking turns leading the pack, can achieve faster speeds for a longer time than any member of the group riding alone. This situation presents each rider in the group with a paradox: winning the race requires cooperation. However, cooperating reduces the amount of energy a rider has at the end to sprint ahead and win the race. Previous research on the physical elements of the sport has produced models that predict individual power requirements for a group of riders under various conditions [1, 4]. These models calculate individual power requirements analytically using fixed pack sizes and rider behavior. In real races, neither pack sizes nor rider behavior is fixed, so a different strategy is needed to model the complex dynamics that can emerge during a race. Traditional multiplayer scenarios assume that all players in the game are equal, and that players in the game are either adversaries or allies for the duration of the game. These approaches do not capture the effect of the varied skill levels among the riders in a dynamical system or shifting alliances.

This complicated, multiplayer game can be captured very naturally in an agent-based model. This article presents such a model that is used to explore the utility of cooperative strategies in a dynamic, competitive environment among heterogeneous individuals. The model, developed with the assistance of the chief physiologist of an International Cycling Union (UCI) professional cycling team, employs rider agents whose properties match the physiology of professional cyclists. These agents act and interact in a simulated bicycle race, following established strategic rules of the sport. The results of the model accurately replicate existing physical effects in racing, both at the microscale (individual) and at the macroscale (team). They offer insights into the effects of different choices, and the relationship between these choices and the nonlinear power/performance equations that operationalize a rider's fitness.

Cooperation in multiplayer games has most often been studied as a two-person Prisoner's Dilemma game. In competitive cycling, spatial proximity, team affinity, personal alliances, and skill level all contribute to who chooses to cooperate with whom. There are examples in the literature of cooperation dynamics similar to those in professional cycling [5]. There are spatial $n$-player ($n \geq 2$) Prisoner's Dilemma studies, where players interact on a two-dimensional spatial array [6]. Many of these studies use networks or cellular automata to examine the evolution of cooperation in a heterogeneous population. The heterogeneous properties have included number of contacts [7], wealth [8], and cooperation strategy [9]. In some studies, agents were mobile [10]. In many of these studies, an agent's payoff was determined by the agent's fitness and proximity to other agents. There has also been research on coalitions and team performance. Researchers have noted that cooperative coalitions can arise within competitive environments in which size or strength of individuals can affect outcome [11–13]. In studies on team performance, the team is created to accomplish a task and all team members are working toward a shared goal [14–16]. There are no individual defections from the team. To date, cycling as a Prisoner's Dilemma has received only anecdotal treatment [17, 18]. Little analytical work has been conducted to assess the effect of cooperative cycling strategies for different skill levels.

## 2. AN AGENT-BASED MODEL

Agent-based models are a good way to describe and investigate systems of individuals (the "agents") whose global (group) dynamics emerge from simple interactions between the individuals [19]. The individuals are described according to a collection (generally small) of features. These features and rules are selected to provide enough detail to simulate a real-world system, but not so much detail that the model is unable to generalize, or is overwhelmed by computational complexity. The dynamics present in a real bike race are ideally matched to this representation. Riders are autonomous individuals with physical attributes, such as power output and knowledge of strategy, that define their cycling ability. Riders also possess personal attributes, such as a willingness to abide by social norms governing interactions between riders in a race. All of these attributes were incorporated into the model described in this article. Each rider in a real race, for instance, has a maximum power output that determines how long and how fast he or she can travel. Similarly, each agent in the model has a maximum power attribute, which is set to match that of a typical professional male cyclist. Agents in this model interact with other nearby rider agents following a set of rules. The agents can choose to cooperate with each other by riding together and taking turns leading the pack. Or, agents can choose to defect either by not taking their turn at the front or by breaking away from the pack. Team dynamics also play an important role: as in real races, teammates help one another, e.g., by sharing the task of leading the pack. Each rider's final placement in the simulated race emerges from these interactions and the rider's individual skill level, as it does in real cycling races.

Several simplifications of real-world physical and personal dynamics were made in this model to explore the baseline behavior of bicycle racing. The previously mentioned personal dynamics have been simplified: each rider's willingness to cooperate is represented probabilistically in a normally distributed field. Rider agents do not engage in any punishments or repeated games, or harbor grudges that could dictate their behavior toward other agents. The primary simplification of the physical dynamics is that the course is flat, all rider agents are the same size, and there are no additional environmental challenges, such as crosswinds. A rider's



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willingness to follow a teammate in a breakaway is also represented probabilistically, instead of being driven by team strategy. Even this simplified model produced results that would be familiar to the director of any professional cycling team.[1]

The physical dynamics of the model are based on power equations that were shown in previous research to replicate power outputs and race times for a real professional bike race [1]. The power required to overcome air and rolling resistance is given by

$$P_{\mathrm{air}} = k\mathrm{CF}_{\mathrm{draft}} v^3 \tag{1}$$

$$P_{\mathrm{roll}} = C_{\mathrm{r}} g(M + M_{\mathrm{b}})v, \tag{2}$$

where $k$ is a parameter that includes variables such as surface area of the rider, wind speed, and road surface, $v$ is velocity in meters per second, and $\mathrm{CF}_{\mathrm{draft}}$ is the drafting coefficient or the percentage decrease in power output due to drafting, $C_{\mathrm{r}}$ is a parameter, $g$ is the gravitational coefficient, $M$ is the mass of the rider, and $M_{\mathrm{b}}$ is the mass of the bike [1]. The total power required is then

$$P_{\mathrm{tot}} = P_{\mathrm{air}} + P_{\mathrm{roll}}. \tag{3}$$

The power output that elite cyclists can sustain until they reach exhaustion can be represented by

$$T_{\mathrm{lim}} = \exp(-6.351 \ln(fVO_{2\,\mathrm{max}}) + 2.478), \tag{4}$$

where $T_{\mathrm{lim}}$ is the time to exhaustion in minutes, and $f\mathrm{VO}_{2\,\mathrm{max}}$ is the fraction of the rider's $\mathrm{VO}_{2\,\mathrm{max}}$ (maximal oxygen consumption) being used [1]. $\mathrm{VO}_{2\,\mathrm{max}}$ can be replaced by 10-min max power, $\mathrm{Max}_{10}$, yielding

$$T_{\mathrm{lim}} = \exp\left(-6.351\ln\left(\frac{P_{\mathrm{tot}}}{\mathrm{Max}_{10}}\right) + 2.478\right), \tag{5}$$

where $\frac{P_{\mathrm{tot}}}{\mathrm{Max}_{10}}$ is the power output needed to travel at a given $v$, expressed as a fraction of the rider's max power output. The $P_{\mathrm{tot}}$ given above can be used to represent a rider's average power output for 1 min. Then, a rider's $T_{\mathrm{lim}}$ in a simulated race can be calculated after each minute in the race based on his power output in that minute.

Agents have a variety of properties, some of which are fixed by the physics and physiology, and some of which are varied across the experiments reported in the following section.

$\mathrm{Max}_{10}$: The 10-min max power (W/kg) that a rider can generate. This represents a rider's skill level and is varied to represent riders above and below the mean in a normally distributed field.

$S_{\mathrm{m}}$: Speed that a rider can travel alone at $\mathrm{Max}_{10}$ power output (m/s).

$E_{\mathrm{rem}}$: The number of seconds a rider has until exhaustion. Based on the $T_{\mathrm{lim}}$ equation above, all riders start the race with the ability to travel at their $\mathrm{Max}_{10}$ for ~715 s.

$C_{\mathrm{b}}$: Cooperation probability, percentage of time that a rider cooperates with other riders in a pack.

$C_{\mathrm{t}}$: Team cooperation probability, percentage of time that a rider follows a teammate on a breakaway.

$B$: Breakaway state. Defecting riders will always break away from the pack when their $S_{\mathrm{m}} * 0.8$ is greater than the speed of the pack by increasing their speed to their $S_{\mathrm{m}} * 0.9$ for 3 min or until they catch up to another pack, whichever comes first. This represents a speed that is noticeably above their anaerobic threshold, but still not at their max power output.

$S$: Speed that a rider is currently traveling. When a rider is in a pack, the rider's speed is the speed of the pack, which is the mean $S_{\mathrm{m}} * 0.8$ of the riders in the pack. This speed puts the pack leader likely above his anaerobic threshold and the rest of the pack below theirs [20].

$D$: Distance that a rider has traveled since the beginning of the race. Used to determine a rider's position in the race as well as generate packs. Riders within 3 m of each other are assigned to the same pack, per UCI rules.

In addition to the agent properties, the model has several overall properties. All simulated races are 160 km, a representative length for a 1-day professional stage race. The pack, containing 15 teams of 10 riders, starts together. Cooperators spend 5 min at the front of the pack, then rotate to the back to rest, and the next rider in line then rotates to the front. If this rider is a cooperator, he also leads the pack for 5 min. If he is a defector, however, he rotates to the back after only 1 min. Although the time scales here are somewhat distorted—riders generally rotate after tens of seconds, not minutes—the ratio, which is the critical element in this model, is realistic.

In the last kilometers of the race, the strategy changes. All riders are trying to cross the finish line with no energy remaining. To model this, agents in the model ride at a stepped percentage of their $S_{\mathrm{m}}$ for the last 5 km of the race, based on their remaining energy. If they can maintain that speed for 1 min, they ride at 100% of $S_{\mathrm{m}}$. If they have 30–60 sec of energy remaining ($E_{\mathrm{rem}} = 30$), they ride at 90% $S_{\mathrm{m}}$; if $0 \leq E_{\mathrm{rem}} \leq 30$, they ride at 70% $S_{\mathrm{m}}$, which is just below anaerobic threshold and should allow for some recovery. Riders with negative energy—those who have gone past the point of exhaustion—ride at 50% $S_{\mathrm{m}}$, significantly below their anaerobic threshold. This set of inequalities matches observed behavior (and power meter data) in UCI professional races.

[1] *Coauthor Lim, the source of this assertion, has more than a decade of coaching experience in the procycling peloton.*


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The bike races being modeled here generally last about 4 h; a time step of 1 min is fine-grained enough to accurately capture the dynamics in a race of this duration. At each time step, the following algorithm is executed:

**Determine cooperators:** Every 5th min, use each rider's base cooperation probability and team cooperation probability to determine whether they will behave as a cooperator or a defector.

**Generate new packs:** Generate packs by grouping riders together that are within 3 m of each other.

**Identify lead riders:** Each pack has a lead rider. If the lead rider is a defector, shuffle him to the back. If he is a cooperator, decrement his time remaining at the front or move him to the back if he has led for 5 min.

**Update rider speeds:** Assign each rider in a pack the same speed.

**Update rider distances:** Add the distance traveled in the last minute ($S * 60/1000$, in km) to the distance $D$ traveled since the beginning of the race.

**Update rider effort:** Calculate the new $T_{\mathrm{lim}}$ based on the power output in the current minute.

The algorithm is executed until the last rider crosses the finish line.

## 3. EXPERIMENTS

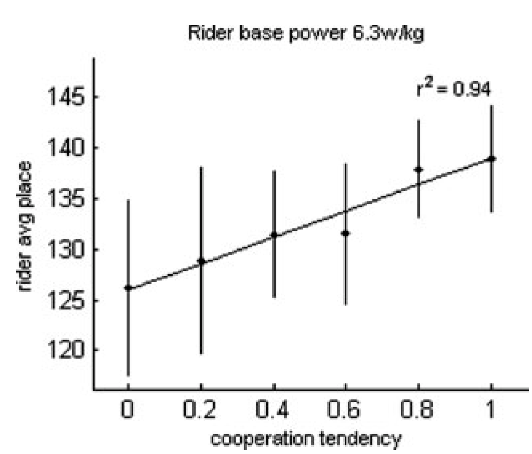
We performed a series of experiments using the setup described in the previous section, varying parameters to explore a realistic range of situations and behaviors. In all cases, the race included 150 riders with normally distributed $\mathrm{Max}_{10}$, $\mu = 7.1\,\mathrm{W/kg}$, $\sigma = 0.4\,\mathrm{W/kg}$. A $\mathrm{Max}_{10}$ of 7.1 W/kg translates to a speed of ~48 kph on flat ground for a 63-kg rider. The cooperation tendencies of the field were also normally distributed—$\mu = 0.48$ and $\sigma = 0.2$—the tendency of the field was to cooperate about half the time. In each model run, one target rider in the field was chosen for closer study, and his $\mathrm{Max}_{10}$ and $C_{\mathrm{b}}$ values were modified to explore the effects of varying those parameters: $6.3 \leq \mathrm{Max}_{10} \leq 8.3\,\mathrm{W/kg}$, in increments of 0.4 W/kg, which spans the usual range in a UCI professional race, and $0 \leq C_{\mathrm{b}} \leq 1$, in increments of 0.2, which covers the range of possible cooperation tendencies. To model team effects, nine teammates for the target rider were selected randomly from the rest of the field. To assess the side effects of the target rider's strategy and performance, one of these teammates was modified so as to be an average-fitness ($\mu = 7.1\,\mathrm{W/kg}$) rider who would cooperate with the target rider at all times (i.e., $C_{\mathrm{b}} = 1.0$). Fifty trials were run for each of the 36 [$\mathrm{Max}_{10}, C_{\mathrm{b}}$] combinations for a total of 1800 trials. Each trial ran until all riders crossed the finish line. The final position of the target rider and the target teammate were recorded for each trial. The average final position over the 50 trials for each $\mathrm{Max}_{10}/C_{\mathrm{b}}$ combination was used to determine the best strategy for a given $\mathrm{Max}_{10}$.

## 4. RESULTS

Results of these model runs show that a rider's best cooperation strategy is related to their skill level. Riders with a $\mathrm{Max}_{10}$ of 6.3 W/kg—among the weaker riders in the race—are better off defecting, as shown in Figure 1. However, their strategy does not impact their teammate's final placements. For mid-range riders ($6.7 \leq \mathrm{Max}_{10} \leq 7.1\,\mathrm{W/kg}$), cooperation strategy does not have a significant impact on final placements or the final placements of their teammates. Cooperation is a good strategy for stronger riders ($\mathrm{Max}_{10} \geq 7.5\,\mathrm{W/kg}$), as shown in Figure 2—both for the individual rider and for the team.

These results are consistent with what happens in professional cycling, at the overall time scale (team and rider placement) as well as over the course of the race. The nonlinear relationship between power output and time to exhaustion shown in Eq. (5), for instance, dictates that spending even a brief period at a high power output diminishes a rider's ability to finish strong at the end of the race. A slight increase in power over extended period of time can have a similar impact. These effects are replicated in the model, together with the cooperation strategies that affect them. All riders, for instance, spend the majority of the race at the "recovery" power output level—consistent with power meter data from UCI races. But, rider strength changes the character of how this time is spent. Figures 3 and 4 show the average minutes spent at the $S_{\mathrm{m}} * 0.5$ power level for weak, medium, and strong riders, along with the resulting average time to exhaustion when the minutes occurred. Stronger cooperating riders often ride at this power level even when they are not in need of recovery: i.e., keeping up with the pack does not tax them. This fact is shown in Figure 4, as these riders

**FIGURE 1**




Mean placements for weak riders ($\mathrm{Max}_{10} = 6.3\,\mathrm{W/kg}$), as a function of cooperation strategy. Defection is an effective strategy for these riders.




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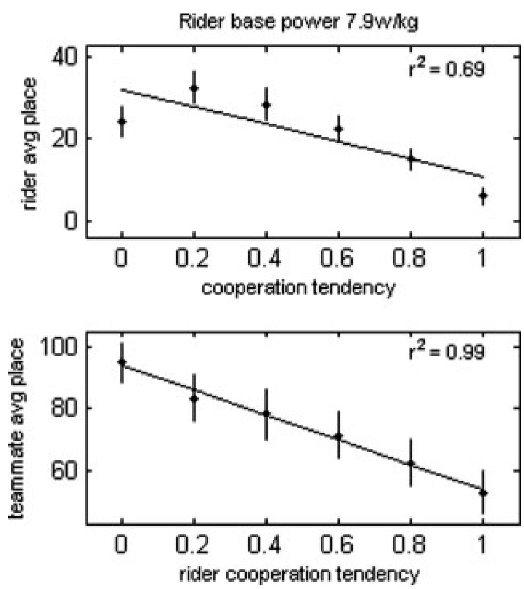
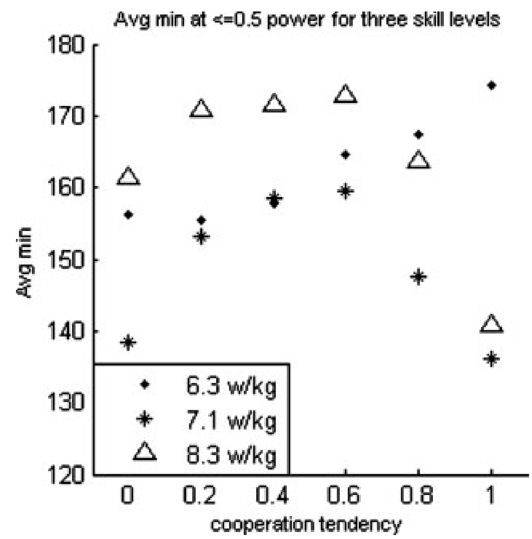
**FIGURE 2**




Mean rider and teammate placements for strong riders ($Max_{10} = 7.9\,W/kg$). When these riders cooperate, they and their teammates finish higher in the race.

**FIGURE 3**

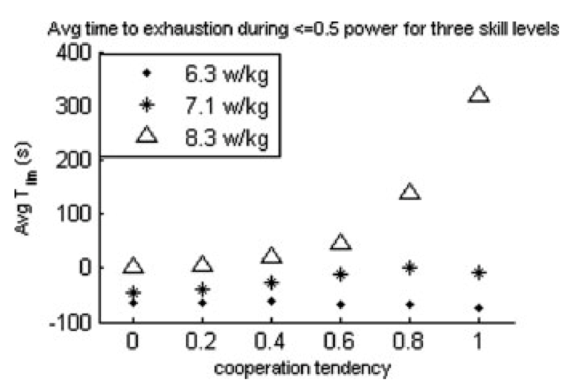



Minutes spent at 50% $S_m$: comparison of 6.3 ($\bullet$), 7.1 ($*$), and 7.9 ($\triangle$) W/kg riders.

still have energy remaining when they are at this power output. However, weaker riders are at this power output because they have already gone past the point of exhaustion and are in recovery. Stronger riders dip into their reserves during the time they spend at the front of the pack, but they are easily able to recover between efforts. For weaker riders, however, being in the pack is not enough to reduce their power output below 50%, even if they take no turns at the front. These riders ride between 50 and 60% of $S_m$ for an average of 50 min of each 250-min race. For these riders, the energy expended at the front of the pack is not offset by time spent in the pack, so energy losses accrue.

Breakaway dynamics are also accurately replicated by this model. Recall that weaker riders are unlikely to initiate a breakaway, but a strong rider can defect by sprinting away from his companions. In real races, and in this model, any cooperating teammates in the pack join the breakaway for support. To accomplish this, they have to match the speed of the lead rider, which may put them (at least temporarily) above their thresholds. In the model, this has the effect of increasing the number of minutes that teammates of defecting riders spend at high effort levels $S_m \geq 0.9$. Teammates of defecting strong riders spend twice as many minutes at this higher power level than do teammates of cooperating strong riders. Riders at effort levels $S_m \geq 0.9$ will reach exhaustion between 23 and 11 min, so spending any additional time at this power output significantly decreases a rider's ability to finish the race without slowing down. The defecting riders themselves, however, spend very few minutes at this higher power output, enabling them to conserve more energy than their cooperating teammates. This could enable these riders to continue racing, even after their teammates have no energy remaining. In real races, even the strongest riders do not have enough energy to break away repeatedly for the entire race. In the model, these riders eventually run out of energy and have to slow down; even someone who is three standard deviations

**FIGURE 4**




Time to exhaustion at 50% $S_m$: comparison of 6.3 ($\bullet$), 7.1 ($*$), and 7.9 ($\triangle$) W/kg riders.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above the mean fitness ($\mathrm{Max}_{10} = 8.3\,\mathrm{W/kg}$) cannot sustain such an uncooperative strategy.

## 5. CONCLUSION

The results and reasoning in the previous section would be completely familiar to directors of UCI professional cycling teams, which is a measure of the success of this model. Its predictions are accurate not only at the scale of individual riders but also at the macroscale of teams and groups of teams. Agent-based models are good at representing systems, like bike races, where the dynamics of the system emerge from individual interactions. Cycling differs from many other team-based activities in that it involves both individual and team accolades, with the result that team members may not always work toward a common goal. This dichotomy is very difficult to model with other approaches, but an agent-based approach can capture it very naturally.

The model presented here is simplified; it does not represent the full range and subtlety of professional cycling. In a real race, for instance, repeated defection would not be tolerated. Therefore, even though this model may suggest that defection is the best strategy, a real rider would not be able to adopt this strategy for very long. In addition, there is a degree of centralized control in real races that is not represented here. In the Tour de France, for example, team directors monitor the race and advise riders on their best strategy, given the positions of their teammates and the goals of the team. The decentralized, agent-based model used here does not incorporate this kind of global knowledge and control. A better approach might be a hierarchical agent-based model, with team directors as agents and riders as subagents. The rider agents would still be subject to the physical demands of cycling and the impacts of local interactions; the director agents would guide the rider agents, following team strategy and using more extensive knowledge of the system. Such a model could be used to explore team strategies: e.g., whether a carefully planned defection by a strong rider could increase a team's chance of winning the race, or whether having two strong riders (viz., Armstrong and Contador) is better or worse than having just one. No model can capture the full range of human nature, however, and unplanned defections could still have a negative impact on the rider's teammates. In the 2009 Tour de France, the race leader, Alberto Contador, defected on his teammate Andreas Kloden, which may have knocked Kloden from a podium position. The impact on Kloden is consistent with the results presented in this article, and a team strategy model would also most likely recommend against such a defection.

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