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RESEARCH ARTICLE **Open Access**

Wind speed, wind yaw and the aerodynamic drag acting on a bicycle and rider

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Abstract

A large portion of a cyclist's power is consumed by *air drag*. Opposing force power meters measure air drag with a wind sensor. In cross winds the bicycle and rider experience a different air drag than that informed by a conventional wind sensor. The main objective of this study is to quantify this error as a function of wind yaw. Additionally, if power is independently measured with a direct force power meter, we estimate the drag area (C_dA) as a function of wind yaw without using a yaw sensor. 1- We use exact equations to estimate air drag from *airspeed* and *wind yaw* instead of approximate equations and a conventional wind sensor that responds to the axial component of the airspeed called *inline airspeed*. 2- We describe a novel method for estimating air drag using a conventional wind sensor under naturally-occurring wind conditions, where the missing wind yaw data is inferred from ground speed, heading and the *prevailing wind velocity.* The prevailing wind is identified as a vector by analyzing ground speed, inline air speed and heading data. Wind yaw that is estimated by this method is called the *virtual wind yaw*. Our test results suggest that a state-of-the-art opposing force power meter, namely the iBike Newton, systematically underreports the total power when the wind yaw is large. We show that the *virtual wind yaw* approximation often returns a more accurate estimate of instantaneous power than a conventional opposing force power meter. When a bicycle is equipped with a speedometer, an inclinometer, a conventional wind sensor and a direct force power meter, the redundancy in the data allows us to determine the constituent components of the total power including the aerodynamic power. It also allows us to determine the C_dA as a function of wind yaw, as well as the time and energy spent within a given range of wind yaw angles. The accuracy of an opposing force power meter can be improved by using exact equations with input from a wind yaw sensor (e.g., a wind vane).

Keywords: bicycle instrumentation, cycling, aerodynamics, air drag, CdA, wind yaw, apparent wind, power meter, OFPM, iBike.

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Introduction

Equations for calculating the power output of a cyclist under no-wind and direct headwind conditions are given by Whitt and Wilson (1974). The 3rd edition of the book, Wilson and Papadopoulos (2004), discusses "rules of thumb" for direct cross winds, and suggests that faired (streamlined) vehicles can generate thrust from cross winds. Isvan (1984) gives equations for the power needed for riding unfaired bicycles under arbitrary wind conditions. Brandt (1998) compares the predictions of these equations with wind tunnel data given by Douglas Milliken (1987) and draws practical conclusions relevant to road cycling. In all cases the power required to move a bicycle at a given speed is a nonlinear function of the wind velocity. That is, both the magnitude and the direction of the mass flow rate relative to the bicycle are relevant.

Bicycle power meters have become available to consumers, and some cyclists use them for real time feedback and training purposes. Power is the product of force and velocity (torque and angular velocity for rotating components). All cycling power meters estimate power by effectively calculating this product, but they are differentiated by which quantities are measured and which ones are inferred. In Direct Force Power Meters (DFPMs), torque is inferred typically by measuring mechanical strains in a rotating drive train component such as a crank arm or wheel hub. This torque is then multiplied with the rotational speed of the component to calculate power. Cycling power is expanded against distinct categories of opposing forces that arise from climbing, air resistance, accelerations, etc. Martin et al (1998) define these power components and construct a mathematical model for estimating the total cycling power and itemizing its components. In Opposing Force Power Meters (OFPMs) propulsion force is inferred by measuring hill slope, bike speed, acceleration and wind resistance, and using these values in equations that include user-specific calibration constants. The total opposing force is then multiplied with the bike speed to estimate power.

Compared to DFPMs, OFPMs offer the benefit of potentially itemizing the constituent components of power (Equation 4), although the OFPMs that are commercially available at the present time do not itemize all of them. OFPMs also tend to be less expensive and do not require modifying or replacing original components of the bicycle. But whether an OFPM can estimate power as accurately as a DFPM is a matter of debate.

One of the factors that limit the accuracy of conventional OFPMs is the attempt to estimate air drag without measuring the wind direction. We analyze the performance of a state-of-the-art OFPM, the iBike Newton™ relative to a DFPM (PowerTap®) and provide evidence of a correlation between the relative discrepancy of their readings, however small, and wind yaw. Wind yaw (apparent wind angle) is the angle of the airflow relative to the direction of travel, which can be measured, for example, with a bicycle-mounted wind vane. A 3-way comparison between a DFPM (PowerTap) and two OFPMs (iBike Newton and Power Analyzer) on two test rides confirms that the iBike Newton's measurement discrepancy relative to the PowerTap is consistent with the use of approximate equations to calculate power from the inline component of the apparent wind. Power Analyzer is a post-processor, developed by the author, which calculates power using *exact equations* where wind yaw (i.e., apparent wind angle) is an input variable. If the recorded ride data does not include wind yaw, Power Analyzer infers it from the *prevailing wind* calculated from ground speed, air speed and heading data (see Figures 2, 7 and 8). This inferred variable is called the *virtual wind yaw*. With strong and steady winds, when the wind yaw data is set to 0°, Power Analyzer's estimate of power is closer to the iBike (Figure 1). With *virtual wind yaw*, it is closer to the PowerTap (Figure 11).

The Virtual Apparent Wind model is still an approximation, because the instantaneous wind velocity is, in general, different than the prevailing wind velocity. But when the wind is strong and steady, as it was during the test rides chosen for this study, the Virtual Wind Yaw model is significantly more accurate than the scalar wind model implemented in the iBike Newton (Table 1). It stands to reason that even more accurate power measurements would be achieved with an OFPM if the wind yaw were *measured* (e.g., with a wind vane) instead of being estimated from the prevailing wind. Furthermore, when neither the actual wind yaw nor the prevailing wind can be measured with on-board instruments, the application of the Virtual Wind Yaw method and the use of exact equations (Equation 1) would likely lead to greater OFPM accuracy than approximate equations, if the prevailing wind data could be obtained from a meteorological database.

Background

The wind sensor used in iBike power meters is a differential pressure sensor (Pitot tube) that responds to the stagnation pressure generated by the inline or axial ("front-to-back") component of the mass flow rate of the airflow relative to the bicycle. This technology is successfully used in aviation instruments to measure *airspeed*, which is a scalar quantity. In aviation, heading and track are two different variables. Heading

Table 1. Comparison of OFPM models and sensor configurations relative to the DFPM .

Description of the OFPM model	Model assumes that air drag is proportional to	% of time with greater than 30% discrepancy to DFPM power
Scalar wind approximation (iBike Newton with cross fin)	$(OB)^2$	17.4%
Scalar wind approximation (iBike Newton without cross fin)	$(OB)^2$	8.6%
Virtual apparent wind approximation (cylindrical model)	$(OC')^2 \cdot \cos(AOC')$	4.7%
Virtual apparent wind approximation (variable CdA model)	$(OC')^2 \cdot \cos(AOC') \cdot \lambda$	2.9%
Exact Solution with vector wind sensor (cylindrical model)	$(OC)^2 \cdot \cos(AOC)$	--
Exact Solution with vector wind sensor (variable CdA model)	$(OC)^2 \cdot \cos(AOC) \cdot \lambda$	--

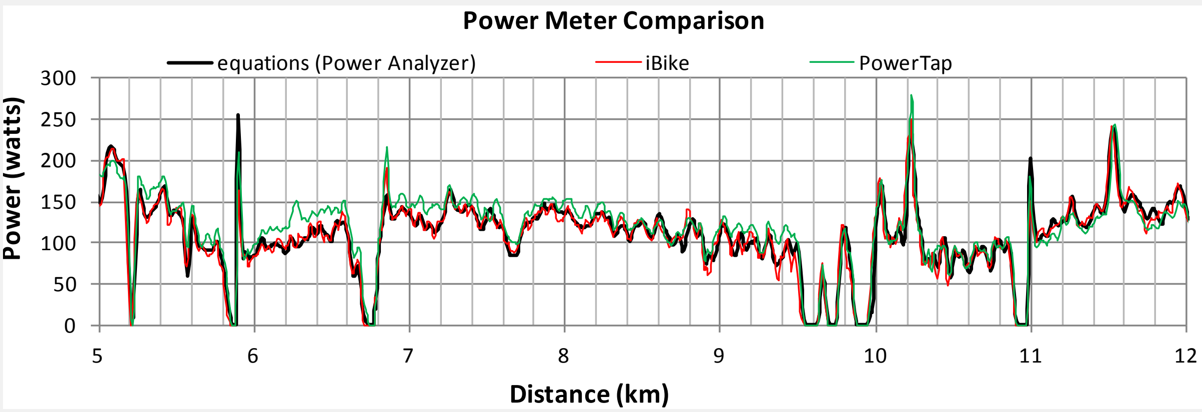

Figure 1. Power estimates from an OFPM (iBike –red curve), a DFPM (PowerTap –green curve), and from exact equations (Power Analyzer –black curve) where wind yaw is intentionally set to 0° to predict the iBike's behavior.

is the direction that the nose of the airplane is pointed at; track is the direction of the plane's movement with respect to the ground. In normal flight heading and track are generally different so that the apparent wind is always a direct headwind (there is no wind yaw). In contrast, a bicycle interacts with two media (ground and air), and normally the wheels roll on the ground without significant side slip. As a consequence, a bicycle's heading and track are always the same, and the apparent wind velocity is a vector with an angle relative to the bike. This angle is called wind yaw. In this respect bicycles have more in common with sailboats than with airplanes. The keel of a sailboat is the equivalent of the wheels of the bicycle.

Because the maximum sensitivity axis of the wind sensor of a conventional OFPM coincides with the direction of the air drag we wish to measure, it is tempting to assume that the air drag acting on the bicycle and rider could be estimated from the output of this sensor without a need to measure the wind yaw. But there are two reasons why this assumption is not valid.

C_dA (a.k.a drag area) depends on wind yaw. For a person riding a bicycle, the front-C_dA is generally smaller than the side-C_dA. Front-C_dA applies when the wind yaw is 0° (*e.g.*, with direct headwinds or when there is no wind). The angle-dependence of C_dA is more significant for recumbent and tandem bicycles, bicycles with "aero bars", disc wheels, bladed spokes, etc, than for conventional road racing bikes. But it is significant for all types of bicycles (Martin *et al*, 1998).

Even with simplified aerodynamic models where C_dA is assumed to be constant with wind yaw (the object dragged through the air is modeled as a vertical cylinder), air drag is proportional to the axial component of the squared airspeed; it is *not* proportional to the square of the axial component of the airspeed. A forward-facing Pitot tube measures the latter quantity instead of the former. This situation may be visualized with the help of Figure 2 where the scalar quantity that the iBike power meter records as "wind speed" is represented by the length of the base of the big triangle (the horizontal blue arrow). But in order to compute air drag accurately, the hypotenuse of the triangle (the apparent wind velocity) must be known as a *vector*. The square of the hypotenuse represents the aerodynamic force, and air drag is the projection of this force onto the direction of travel. In mathematical terms where w represents the magnitude and β the angle of the apparent wind velocity, the quantity ($w^2 \cos \beta$) and the quantity ($w \cos \beta)^2$ are not equal. Air drag is proportional to the former quantity, but conventional OFPMs measure the latter quantity instead. For sufficiently small wind yaw angles (β) this error may be negligibly small, but as the wind yaw angle grows, so does the error.

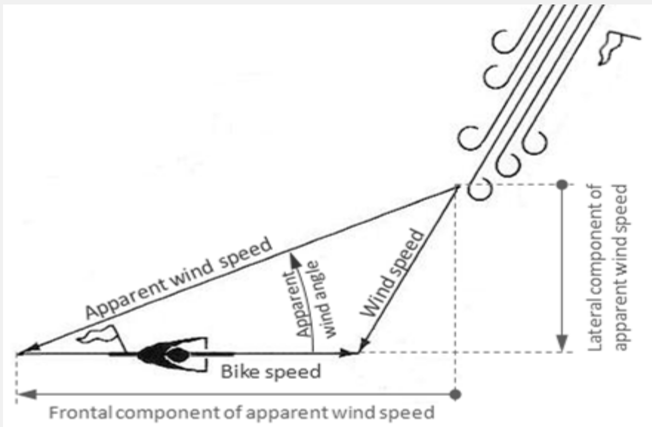

Figure 2. Birdseye view of the cyclist with a graphical representation of the physical relationships between wind speed, bike speed, apparent wind speed and apparent wind angle (wind yaw). Note the different wind directions indicated by flags on the ground and on the moving bicycle.

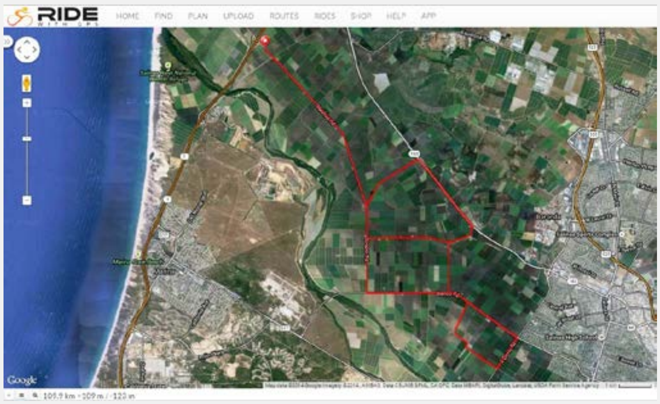

Figure 3. Aerial view and GPS track of the test course.

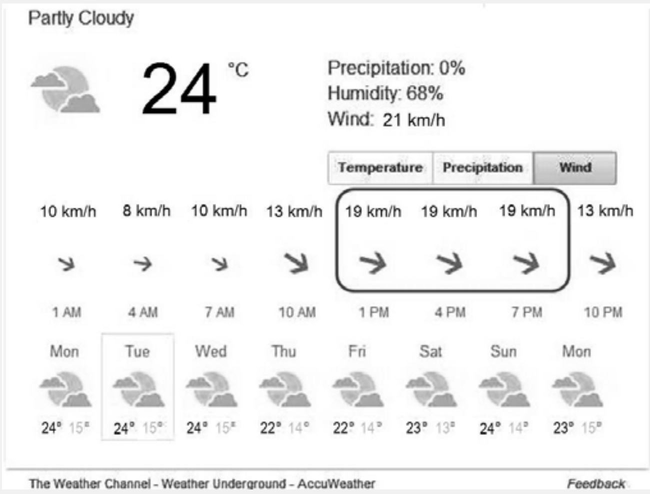

Figure 4. Weather forecast for the test ride. The red rectangle identifies the time window chosen for the test.

Figure 5. Example snapshot from the test ride.

This error is rooted in the fact that force is a vector, while pressure (normal force per area) is a scalar. This may be visualized by the following consideration: conventional OFPM technology is based on the principle of measuring the air drag with a measurement probe. A forward-facing Pitot tube, such as the wind sensor used in the iBike Newton power meter, is equivalent to a load cell that measures the normal force acting on a *flat* measurement probe held perpendicular to the direction of travel. But for the measured quantity to scale with the air drag acting on the bicycle and rider, the probe must not be flat. The ideal probe would have the same 3D aerodynamic profile as the bicycle and rider, and the load cell would measure the *axial component* of the force acting on the probe.

smoothing window =	0	seconds
moving time = 4:10:46	15046	seconds
distance =	110.3	km
elevation gain =	166	m
average speed =	26.4	km/h
r.m.s. "wind speed" =	13.7	km/h
upwind heading =	54	%

workload category	avg. watts	Energy kJ	%
gravity	7.5	112	5.1%
aero	98.5	1482	66.7%
rolling	24.2	364	16.4%
inertia	14.9	224	10.1%
drivetrain losses	2.7	41	1.8%
Power Analyzer	147.7	2223	100.0%
iBike	140.6	2116	95.2%
PowerTap	146.9	2211	99.5%
wasted in brakes	0.5	8	0.3%
provided by wind	-16.4	-247	-11.1%

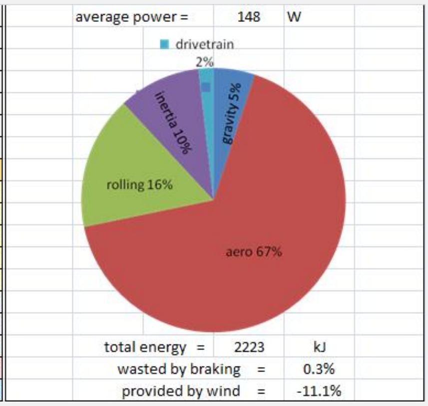

Figure 6. Some of the relevant statistics of the test ride with cross fin (screenshot from Power Analyzer).

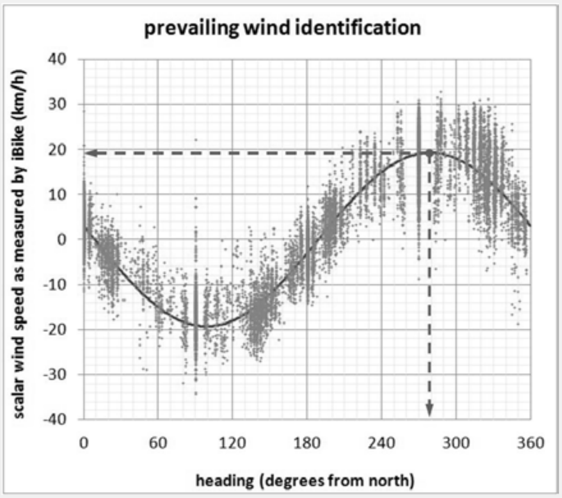

Figure 7. Identifying the prevailing wind as a vector

To reduce the error in cross winds imposed by these two factors, the iBike Newton power meter features a passive component called a "cross fin". The intended purpose of this part is to locally modify the airflow in the vicinity of the air intake of the wind sensor in such a way that the sensor's output remains proportional to the air drag acting on the bike and rider across a wide range of wind yaw angles.

In theory the cross-fin solution seems plausible. However, when the output of an iBike Newton (OFPM with cross fin) was compared with that of a reference DFPM (PowerTap), it was observed that sometimes the iBike reports less power than the PowerTap. Figure 1 illustrates an example of this phenomenon. Note the relatively poor agreement around the 6 – 7 km mark. In a normal bike ride this happens in rather rare occasions. Our hypothesis is that the discrepancy results from the use of a scalar wind sensor and approximate equations that systematically underestimate the air drag when the wind yaw is large.

The original objective for this project was to test this hypothesis by looking for a statistical correlation between large wind yaw angles and large discrepancies between the readings of OFPMs and DFPMs. While performing test rides for this purpose it became evident that in the absence of an instrument to measure wind direction, the (unknown) wind yaw can be estimated from the scalar wind speed measured with the iBike power meter, provided that the speed and direction of the bike and the *prevailing wind* are also known. Furthermore, it was discovered that by substituting this estimated *virtual apparent wind* for the *instantaneous* apparent wind in the exact equations, the instantaneous power is estimated with greater accuracy than with the iBike Newton with or without the cross fin. This discovery became the subject of further investigation that led to the development of an algorithm for improving the accuracy of an OFPM *without* using a wind direction sensor. It also paved the way to developing a method for determining the C_dA of a person riding a bicycle as a function of wind yaw

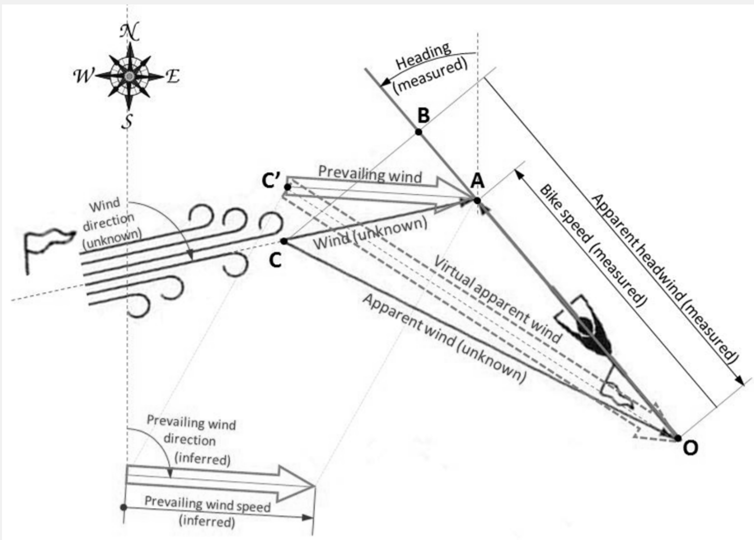

Figure 8 The instantaneous Virtual Apparent Wind velocity (Line C'O) is computed from the prevailing wind velocity (Line C'A) and bike speed (Line OA). Point C' is an approximation to the unknown point C.

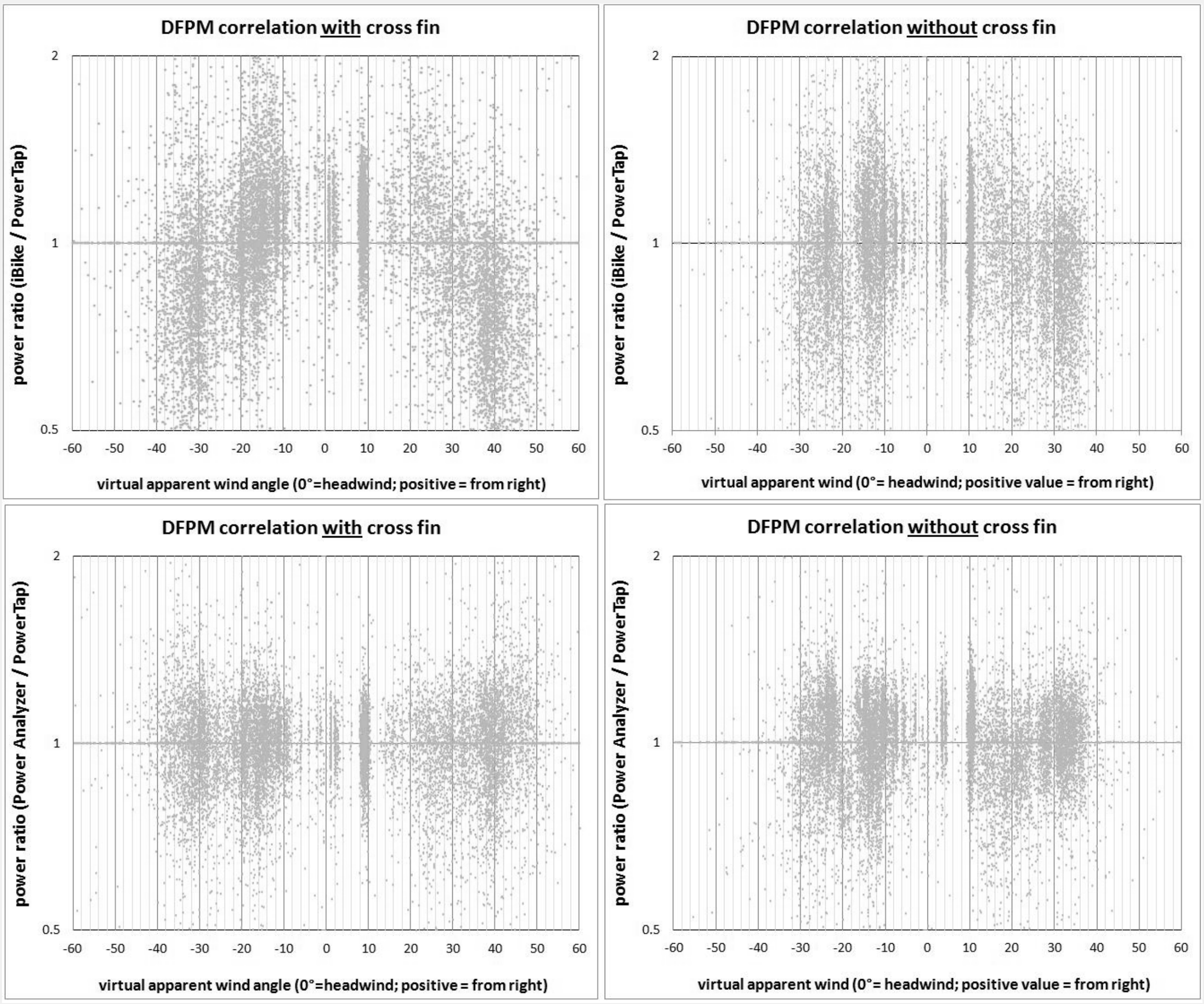

Figure 9. Comparison between two power estimation methods for OFPMs: Scalar Wind method represented by iBike, and Virtual Apparent Wind method represented by Power Analyzer.

(apparent wind angle) without using a wind tunnel, from ride data recorded during a bike ride.

It should be noted that this method for estimating the virtual apparent wind vector requires a sufficiently long period of strong and steady wind conditions that are persistent throughout the course. Such conditions are rarely the case in normal cycling.

Test method and results

We wanted to test our hypothesis with an instrumented bicycle, but an instrument to measure the wind yaw and record it in sync with OFPM and DFPM data was not available. This led to the idea of calculating wind yaw from the *prevailing* wind velocity, which could be inferred from the recorded "wind speed" (i.e., inline airspeed) and heading data. The idea was that since the instantaneous wind direction relative to the ground has a greater likelihood of coinciding with the prevailing wind direction than with the bicycle's heading, exact equations with this "virtual apparent wind" would have a greater likelihood of returning an accurate estimate of air drag (and consequently power), than the approximate equations implemented in conventional OFPMs. This hypothesis was tested with two test rides (one with, one without cross-fin) that meet the following requirements:

Strong and steady wind in an open area free of obstructions

Numerous headings in as many directions as possible

Flat terrain (air drag must be the principal constituent of the total opposing force).

Low traffic density.

A 110 km test course that meets these requirements is shown in Figure 3.

The course was laid out on a grid of farm roads with 3 rectangular loops that are angled relative to each other so that the course includes as many headings as possible. For each of the 2 test rides, each of the 3 loops was ridden twice in each direction (clockwise and counterclockwise) resulting in a total of 12 loops over approximately 110 kilometers ridden in approximately 4 hours. Wind conditions forecasted for the duration of the test ride with the cross fin is shown in Figure 4. The test ride without the cross fin was performed under similar conditions.

A snapshot from the video recording of the test is given in Figure 5 to illustrate the favorable conditions.

After the test ride, the recorded data was analyzed. Figure 6 includes selected statistics, which are given

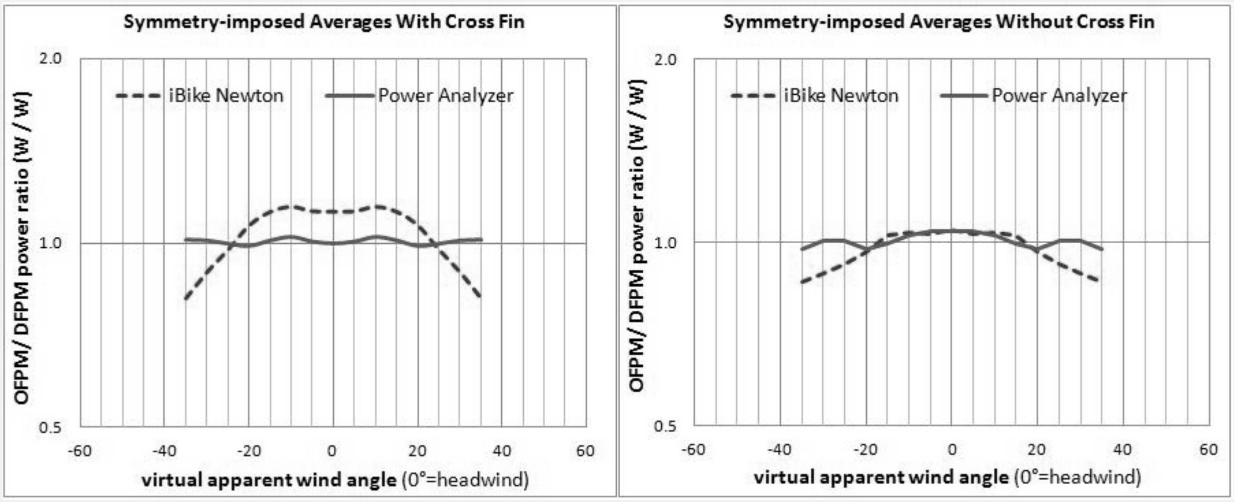

Figure 10. Power ratio as a function of wind yaw. The value at 0° reflects the power meter's sensitivity calibration, which is not the subject of this study but given for completeness. We pay attention only to the normalized shape of the curves

for reference only. The large share of the aerodynamic energy should be noted.

Data synchronization

The ride data recorded by the iBike Newton power meter includes (among others) the following variables:

Axial projection of the apparent wind velocity, a scalar variable indicated by the horizontal blue arrow in Figure 2. In the iBike documentation this scalar is called "wind speed", but we refer to it as the *inline airspeed.*

- Hill slope
- Bike speed
- iBike-estimated power
- PowerTap-estimated power.

The data acquisition rate was set to 1 sample per second.

The iBike-proprietary data file is uploaded to a personal computer, analyzed using iBike's Isaac software, and exported as a data file in CSV (Comma Separated Values) format. In addition to the variables recorded by the iBike Newton power meter, the exported CSV file also contains GPS location coordinates downloaded from the iBike Cloud, which have been recorded during the test ride by iBike's Newton Tracker app running in a mobile phone located in the rider's pocket. These location coordinates are automatically synched with the rest of the ride data by the Isaac software. The CSV file contains all the input data for Power Analyzer, which is a spreadsheet program.

Prevailing wind

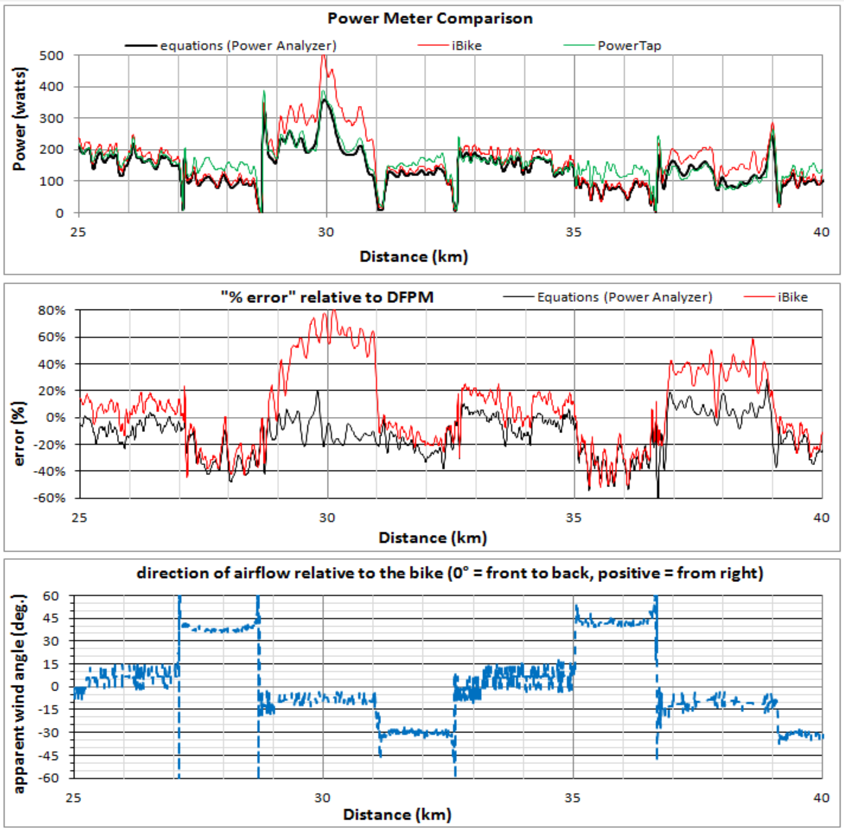

Figure 11. 3-way comparison between a DFPM (PowerTap), the Scalar Wind model (iBike), and the Virtual Apparent Wind model with variable CdA and μ = 1.2. The lowest trace shows the virtual apparent wind angle. The actual apparent wind angle was not measured.

The first step of our analysis is the identification of the prevailing wind. Figure 7 is a scatter chart of the iBike-measured scalar "wind speed" that we call the inline airspeed, plotted against heading.

Each point on the red curve in Figure 7 is the average of all scatter points (green dots) that have headings within ±5 degrees of the point being plotted. Thus, the *speed* and *direction* of the prevailing wind velocity are indicated by the *vertical* and *horizontal* coordinates, respectively, of the peak value of the red curve. For the ride under investigation, these values are 19.3 km/h and

283 degrees, respectively. It was noted that these values concur with the regional weather forecast (Figure 4) obtained prior to the ride.

Virtual Apparent Wind

Because the ride data does not include the apparent wind velocity (coordinates of Point C in Figure 8) for each data sample, these values are estimated from the prevailing wind vector identified in the previous step. The resulting vector (C'O) is called the "virtual" apparent wind velocity. In effect we use the virtual point C' as an approximation to the unknown point C. The rationale for this process is the following:

The power estimation algorithm used in the iBike Newton returns results that are consistent with an assumption that air drag is proportional to the square of the length of Line OB in Figure 8. Indeed, when the apparent wind angle *(AOC)* is sufficiently small, the difference between the quantities [$(OB)^2$] (Scalar Wind approximation used by iBike) and [$(OC)^2 \cdot \cos(AOC)$] (exact solution for constant C_dA –i.e., the cylindrical aerodynamic model) becomes negligibly small. But with strong cross winds or quartering tailwinds the apparent wind angle *(BOC)* can be arbitrarily large, in which case the Scalar Wind approximation would result in underestimating the air drag.

In addition, with strong cross winds the exact equations applied to the cylindrical model would also underestimate the air drag, because a person riding a bicycle is an object that is somewhat streamlined in the forward direction.

Our solution is to estimate the apparent wind velocity (Line CO) as a vector. The *prevailing wind velocity*, inferred from ride statistics *as a vector* as illustrated in Figure 7, is represented by the arrow at the lower left corner of Figure 8. The vector equations used in Power Analyzer for computing the virtual apparent wind velocity (Equations 1 and 2) are graphically analogous to parallel-moving this arrow and inserting it into the vector diagram as Line (C'A). The resulting *virtual apparent wind* velocity, Line (C'O), is used as an approximation to the unknown *apparent wind* velocity, Line (CO).

It was found that for the two test rides conducted for this study (one with, one without cross fin), the *virtual apparent wind approximation* results in significantly less error in power than the scalar wind approximation. Perhaps more importantly, modeling the wind velocity as a vector allows us to use C_dA values that are variable according to a predetermined function of the apparent wind angle (wind yaw), which results in further reductions in error.

In Table 1, power estimates from two models, the *scalar wind* model and the *virtual apparent wind* model are compared, and their respective "errors" (differences relative to the DFPM) are tabulated. Here, λ is an empirically determined nonlinear function that defines how C_dA changes with apparent wind angle for the particular bicycle and rider –see Equation (2).

In Table 1, the "error" of an OFPM is defined as the percentage of data points where the *absolute value* of the difference between the OFPM and DFPM powers exceeds 3% of the DFPM power (the wind sensor's sensitivity scalar is adjusted until the *mean value* of this difference is reduced to zero). The reduction in this quantity from 17% (scalar wind approximation) to 3% (virtual apparent wind approximation) can be visualized from the scatter plots in Figure 9, where the ratio of OFPM power to DFPM power is plotted for every data sample. The ideal distribution of scatter data would be a maximum density of 1's forming a horizontal cluster. A visual inspection of Figure 9 reveals that Power Analyzer (virtual apparent wind approximation with variable C_dA) approaches that ideal more closely than the iBike Newton (scalar wind approximation with constant C_dA) with or without cross fin. If actual data from a wind direction sensor were available (a wind vane, for example), the exact equations used in Power Analyzer would likely return even more accurate results. It should be noted that for this test to be valid, the reference DFPM (PowerTap) does not need to be accurate; it only needs to be consistent (not affected by wind yaw).

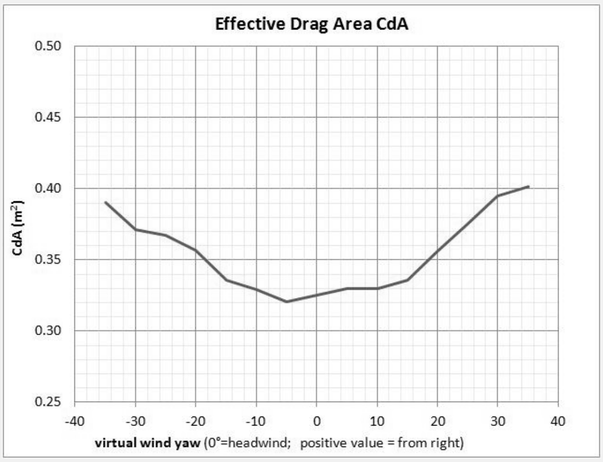

Figure 12. The relationship between CdA and wind yaw

It is noted that the 'cross fin' accessory of the iBike Newton power meter spreads the wind sensor's response across a wider range of wind angles, but this results in a decrease, rather than an increase, in the overall correlation with the DFPM power.

As expected, the application of the variable C_dA model results in better OFPM performance (a significant reduction in the frequency of above-threshold errors, from 4.7% with the cylindrical model to 2.9% with the variable *CdA* model with μ = 1.2).

The statistics for the virtual apparent wind model in Table 1 are drawn from the test ride recorded with the cross fin (the default configuration for the iBike Newton power meter). The variable C_dA method compensates for the effect of the cross fin, because the model parameters are tuned for the particular wind sensor with which the wind was measured. "Parameter tuning" refers to the process of determining the sensor's sensitivity, the speed and direction of the prevailing wind, and the parameter μ that defines the directivity function λ (see Equation 3), so as to minimize the "error" relative to the DFPM, of the total energy (or average power) for the entire test ride.

The directivity function λ is defined by a single constant μ that represents the ratio of side- C_dA to front- C_dA. This constant is called the aerodynamic aspect ratio (Equation 2). For relatively streamlined objects such as recumbent and tandem bicycles, tucked-in racing positions, faired bikes, time trial bikes with aero bars, disc wheels, bladed spokes, etc., this constant is relatively large. For upright riding positions on standard bikes it is relatively small but still greater than 1. For a vertical cylinder, μ = 1.0. For the test ride conducted without the cross fin where the wind sensor is modeled as a standard Pitot tube, the power correlation between Power Analyzer and DFPM reaches a maximum when μ = 1.2.

Figure 10 is made to remove the scatter from Figure 9. Each curve in Figure 10 is made of points representing average OFPM / DFPM power ratios for data samples with virtual apparent wind angles within ±5° of the corresponding horizontal coordinate. The ideal curve would be a horizontal line at 1.0 (total agreement with DFPM).

In Figure 10 negative and positive wind yaw angles have been averaged to impose symmetry in an attempt to suppress random error and highlight systematic error. However, some asymmetry may be caused by the non-symmetric location of the static pressure port of the differential pressure gauge in the iBike Newton power meter.

The more familiar format of presenting ride data as a time sequence (e.g. Figure 11) confirms these results, but it is difficult to see patterns when zoomed out enough to include a statistically relevant number of data points. Therefore, only an exemplary 15 km segment of the 110 km test ride is shown where the effect is particularly noticeable.

The results presented in Figures 9 – 11 are obtained from special test rides designed to maximize the aerodynamic component of the total energy. In typical rides with significant hills and accelerations, these 3 power meters (iBike Newton, Power Analyzer and PowerTap) track each other better, except for the occasional congruence of conditions as shown in Figure 1.

CdA as a function of wind yaw

Just as power can be calculated from ride data when C_dA is given; so can C_dA be calculated when power is given. Thus, if the inline airspeed, GPS heading, hill slope, bike speed and DFPM power have been recorded for a bike ride with a steady prevailing wind, the *Virtual Apparent Wind* method can be applied to express C_dA as a function of wind yaw (Figure 12). Here, the bike and rider parameters are: 179 cm, 64 kg rider, seated pedaling, hands on brake hoods, standard road racing bike, wire-spoked wheels without aerodynamic enhancements.

When interpreting Figure 12 with respect to other studies, two points should be taken into consideration.

Due to the definition of variables, the quantity shown as "drag area" in Table 1 of the article by Martin et al (1998) corresponds to the product of effective drag area and the cosine of wind yaw in our analysis.

Figure 12 is based on the assumption that when the cross fin is removed, an iBike Newton power meter measures the axial component of the mass flow rate (the length of the line segment BO in Figure 8), as would a normal Pitot tube in theory. This assumption is not validated, but Figure 12 is included here to demonstrate the potential utility of the experimental method. For accurate assessment of C_dA *vs* wind yaw, the wind sensor's angular sensitivity pattern (polar directivity function) must be independently known.

The Virtual Apparent Wind method may be used for cross-referencing CFD analysis or wind tunnel test results. For some applications this information may be particularly valuable because statistically relevant data are obtained from actual bike rides on existing roads under naturally occurring wind conditions.

Equations

Air drag F_X is the inline (front-to-back) projection of the aerodynamic force F acting on the bicycle and rider (Equation 1).

Air drag =

$$F_X = F \cdot \cos(\beta) = 0.5 \cdot \rho \cdot C_d \cdot A \cdot w^2 \cdot \cos(\beta) \quad (1)$$

where ρ is air density, and w and β are the apparent wind speed and apparent wind angle (wind yaw), respectively, as illustrated in Figure 2. C_d (effective drag coefficient) and A (effective area) are functions of β. We denote the *frontal* C_dA as $(C_dA)_0$, so that

$$F_X = 0.5 \cdot \rho \cdot [\lambda \cdot (C_d A)_0] \cdot w^2 \cdot \cos(\beta) \quad (2)$$ where

$$\lambda = cos^2 \beta + \mu \, sin^2 \beta \quad (3)$$

is the directivity function, μ being the aerodynamic aspect ratio (the ratio of side-C_dA to front-C_dA) of the particular bike and rider. The value of μ is empirically determined to be ≈ 1.2 for a typical riding position on a standard road racing bike, which was used during both test rides.

Aerodynamic power, P_{aero}, is equal to the product of ground speed u and air drag Fx.

The total power at the pedals, P_{total} is:

$$P_{total} = P_{aero} + P_{climbing} + P_{rolling} + P_{inertia} + P_{mech} \quad (4)$$

The 5 terms to the right of the equal sign are the powers expended against air drag, gravity, tire rolling resistance, inertia and drive-train losses, respectively. $P_{climbing}$ and $P_{inertia}$ are reactive powers that can be positive or negative (uphill or downhill slopes;

accelerating or decelerating). Reactive powers are not dissipated; they may only be stored and / or retrieved. The other 3 power components listed in Equation 4 are resistive powers. Resistive powers are dissipated; they cannot be stored or retrieved. For the test ride with the cross fin, total energies and average values of all positive power components are tabulated under “workload categories” in the pie chart in Figure 6. Braking also dissipates power, but this power is not included in Equation 6 because normally brakes are not applied while simultaneously applying power to the pedals.

Conclusions

Wind yaw angles encountered during normal bike rides can be large enough to compromise the accuracy of an OFPM that utilizes a fixed Pitot tube as the only wind sensor without measuring wind yaw.

It is possible to measure the prevailing wind velocity as a vector, even in the absence of a sensor for measuring wind angle, provided that the wind is steady and the axial (inline-projected) component of the apparent wind velocity, called “inline airspeed” and bike heading are recorded.

Under steady wind conditions, instantaneous wind yaw can be estimated from the inline airspeed, prevailing wind speed and direction, bike speed and bike heading.

If the apparent wind is not measured as a vector but its axial component is measured (i.e., conventional OFPM), using exact equations where the wind yaw is estimated from the prevailing wind (virtual wind yaw) can increase the accuracy of the estimated power.

With special test rides that meet certain prerequisite terrain and wind conditions, C_dA can be estimated as a function of wind yaw even without the use of a wind direction sensor.

Practical applications

We hope that this study will encourage the development of bicycle-mounted inclinometers, accelerometers and wind meters, and promote their use as optional accessories to bike computers and power meters, and to software applications for mobile devices. We also hope that wind sensors used for this purpose will measure the wind velocity as a vector, which might lead to the production of convenient, robust and accurate power meters at a lower cost than direct force measurement alternatives.

The ease of acquiring and sharing wind data during bike rides may raise awareness of wind conditions on typical bike routes, during specific bike rides and competitive events.

Resolving the wind velocity as a vector with respect to the ground opens up the ability to upload wind data from bicycle-based mobile devices to cloud services with the potential of generating crowd-sourced wind maps.

The method developed for measuring CdA as a function of wind yaw, and its potential application to new product R&D may influence the design of aerodynamic bicycle components.

Abbreviations

CdA: Effective Drag Area (product of the aerodynamic drag coefficient Cd and the area perpendicular to the apparent wind velocity)
CFD: Computational Fluid Dynamics
CSV: Comma Separated Values
DFPM: Direct Force Power Meter
GPS: Global Positioning System
OFPM: Opposing Force Power Meter

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References

1. Brandt, J. (1988). Headwinds, Crosswinds and Tailwinds –a Practical Analysis of Aerodynamic Drag. Bike Tech, Vol. 5, August.
2. Isvan, O. (1984). The Effect of Winds on a Bicyclist’s Speed, Bike Tech, Vol. 3, June.
3. Martin, J., Milliken, D., Cobb, J., McFadden, K., Coggan, A. (1998). Validation of a Mathematical Model for Road Cycling Power. Journal of Applied Biomechanics, 14, 276 - 291.
4. Milliken, D. (1987). Bike Tech, August.
5. Whitt, FR. and Wilson, DG. (1974). Bicycling Science. MIT Press.
6. Wilson, DG. and Papadopoulos, J. (2004). Bicycling Science. MIT Press.