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Physical characteristics and resistance parameters of typical urban cyclists

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ABSTRACT

This study investigates the rolling and drag resistance parameters and bicycle and cargo masses of typical urban cyclists. These factors are important for modelling of cyclist speed, power and energy expenditure, with applications including exercise performance, health and safety assessments and transportation network analysis. However, representative values for diverse urban travellers have not been established. Resistance parameters were measured utilizing a field coast-down test for 557 intercepted cyclists in Vancouver, Canada. Masses were also measured, along with other bicycle attributes such as tire pressure and size. The average (standard deviation) of coefficient of rolling resistance, effective frontal area, bicycle plus cargo mass, and bicycle-only mass were 0.0077 (0.0036), 0.559 (0.170) m^2, 18.3 (4.1) kg, and 13.7 (3.3) kg, respectively. The range of measured values is wider and higher than suggested in existing literature, which focusses on sport cyclists. Significant correlations are identified between resistance parameters and rider and bicycle attributes, indicating higher resistance parameters for less sport-oriented cyclists. The findings of this study are important for appropriately characterising the full range of urban cyclists, including commuters and casual riders.

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KEYWORDS
Bicycles; rolling resistance; aerodynamic drag; bicycle mass; coast down test

Introduction

Urban cycling for transportation is incentivised and increasing in many cities of the world. Accordingly, there is growing interest in more detailed and sensitive tools to model all types of bicycle travel at multiple levels, from microsimulation to strategic planning and health impact assessments. Appropriate physical characterisation of urban cyclists is essential for some detailed speed and energy modelling applications, which can be used for health and safety assessments, exercise performance modelling, infrastructure design, transportation network analysis, and more (Bigazzi, 2017; Bigazzi & Figliozzi, 2014, 2015; Mercat, 1999; Mueller et al., 2015; Olds, 2001; Parkin & Rotheram, 2010; Taylor & Mahmassani, 2000; Twaddle, Schendzielorz, & Fakler, 2014). For example, cyclist physical characteristics and resistance parameters have been used to model bicycle speeds for traffic signal timing applications (Tengattini & Bigazzi, 2017) and to model breathing rates for estimation of pollution inhalation and identification of low-exposure cycling routes (Broach & Bigazzi, 2017).

In the absence of wind and mechanical drivetrain losses, cyclist power P can be modelled as

$$P = mgGv + mgC_r v + \frac{1}{2}\rho C_d A_f v^3 \quad (1)$$

where mg is the weight (in N) of the bicycle, cyclist and cargo, C_r (unit-less) is the rolling resistance coefficient (which depends on factors such as tire pressure, tire width, and pavement roughness and material), G is the road grade (unit-less), v is the bicycle ground speed (m/s), ρ is the air density (kg/m^3), and C_d (unit-less) and A_f (m^2) are the drag coefficient and frontal area of the bicycle, cyclist and cargo (Candau et al., 1999; Martin, Milliken, Cobb, McFadden, & Coggan, 1998; Wilson, 2004). The product $C_d A_f$ (m^2) is often referred to as effective frontal area.

Rolling and aerodynamic resistance parameters are fundamental vehicle characteristics that have been extensively studied for motorised vehicles, and to a lesser extent for sport cyclists (Gross, Kyle, & Malewicki, 1983; Olds, 2001; Wilson, 2004). However, no comprehensive research has been carried out to characterise these resistances for the range of real-world urban cyclists (Bigazzi & Figliozzi, 2015; Wilson, 2004). Less sport-oriented and more casual or utilitarian cyclists could have substantially different physical characteristics, which would impact their energy expenditure, speed, travel behaviour, and other exercise and travel-related performance outcomes.

Diverse methods can be used to measure bicycle resistances, but most are impractical for a large-sample study of real-world cyclists. Wind tunnel testing is a common approach, but relatively costly, difficult to apply to a wide range of travellers, and only able to measure drag resistance (Debraux, Grappe, Manolova, & Bertucci, 2011). Data from bicycles instrumented with power-meters to measure cyclist power at different speeds v can be used with Equation (1) to estimate rolling and drag resistance parameters, but again this is difficult to apply to a wide range of travellers, and requires modifying the bicycle for which parameters are sought (Bertucci, Rogier, & Reiserll, 2013; Maier, Müller, Schmid, Steiner, & Wehrlin, 2018). Virtual elevation and dynamometric methods (towing the bicycle on flat ground at constant

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speeds using a cable paired in series with a dynamometer) to estimate rolling and drag resistance parameters would also be impractical in a traveller intercept study (Debraux et al., 2011). Finally, coast-down or deceleration methods can be used to measure rolling and drag resistances, and can be performed in a short amount of time without modifying the test bicycle (Candau et al., 1999; Debraux et al., 2011; Kyle & Bruke, 1984; Macdermid, Fink, & Stannard, 2015).

The primary objective of this paper is to provide researchers and practitioners in several fields (sports science, biomechanics, transportation engineering and planning) with representative distributions of physical parameters for real-world urban cyclists that can readily be used in bicycle performance modelling. Correlations among physical characteristics are also analysed to test the hypothesis that resistance parameters are higher with less sport-oriented attributes of the rider and bicycle.

Methods

Bicycle coast-down test

A recently developed outdoor bicycle coast-down test method is used to measure resistance parameters for intercepted cyclists. The test methodology was chosen because it can be implemented *in situ* without modifying the participant's bicycle and presents minimal burden on participants. In a validation study the outdoor test was less precise than similar indoor testing but still sufficiently sensitive to measure changes in resistance with tire pressure and riding position (Tengattini & Bigazzi, In press).

The testing protocol comprises the coasting of a cyclist from a cruising speed to a stop, through 12 time traps installed on a 100 m stretch of bikeway at 10 m spacing (Figure 1). Time trap sensors (infrared emitter/receiver pairs) record the progression of the bicycle while second-by-second ground wind speed and direction are measured by an anemometer (Young Ultrasonic 2D Anemometer, model 85,000). Grade is surveyed every ten meters with a stadia and a level. Air density is estimated from altitude and temperature using $\rho = \rho_0 \cdot e^{-0.127h} \cdot \left(\frac{273}{T}\right)$, where ρ_0=1.293 kg/m^3, h is altitude above sea level (km) and T is absolute temperature (°K) (di Prampero, 1986).

Rolling and drag resistance parameters C_r and C_dA_f are estimated from measured data based on the physical equation

$$m\frac{dv}{dt} = -mgG - mgC_r - \frac{1}{2}\rho C_d A_f (v - w)|v - w|, \qquad (2)$$

where t is elapsed time (s), w is wind speed in the direction of travel (m/s) and other variables are defined above. Equation (2) is inverted to a second-order differential equation in the time-space domain,

$$\frac{d^2t}{dx^2} = \left(\frac{dt}{dx}\right)^3 \left[gG + gC_r + \frac{1}{2m}\rho C_d A_f \left(\left(\left(\frac{dt}{dx}\right)^{-1} - w \right) \cdot \left| \left(\frac{dt}{dx}\right)^{-1} - w \right| \right) \right] \qquad (3)$$

which can be solved using a finite element method for $t(x)$, the elapsed time at which the cyclist passes the sensor at a distance x (m) from the start of the test. Best-fit resistance parameter values are generated using a genetic algorithm with an objective function to minimize squared error between measured $t(x)$ and $t(x)$ based on Equation (3). Details of the method are given in Tengattini and Bigazzi (In press).

Field test administration

The coast down-test was administered to intercepted cyclists over 18 days in summer 2016 at 9 locations in Vancouver, Canada. Table 1 provides testing session details. All locations were off-street cycling facilities, chosen based on flatness (grade approximatively null), uninterrupted length (at least 100 m long plus 20–30 m for acceleration), and accessing cyclists in a variety of contexts (university, downtown, waterfront paths, and residential areas). Data collection days were all weekdays (Monday-Friday), chosen based on experimenter availability and meteorological conditions (low probability of rain). Data collection times ranged from mid-day to early evening (approximately 12:00 to 19:00) to target peak and off-peak travellers. High-volume locations (over 3,000 bicycle trips per summer-weekday) were avoided during peak periods to minimise disruption on busy bicycle facilities and avoid participant queues (four experimenters together could process at most around 15 participants per hour). Field tests were administered with the approval of the University of British Columbia Research Ethics Board (H16-00604).

Cyclists were first contacted with signage one block in advance of the testing area, followed by research team members with university branding, juice, and snack bars. All cyclists willing to participate were included in the study. After providing consent, participants completed a 3-page questionnaire with socio-demographic and trip-related questions. Simultaneously, participant bicycle characteristics were measured by the research team (make, model, and year, number of gears, tire pressure, tire width, weight, and cargo). Bicycle type was categorised as "road" (drop handlebars, thin smooth tires), "mountain" (flat handlebars, large knobby tires, suspension), "hybrid" (flat handlebars, medium tires), "cruiser" (cruiser handlebars, large smooth tires, upright seating position), and "other" (including e-bikes, tandems, and cargo bicycles). Participants were weighed with all clothing worn

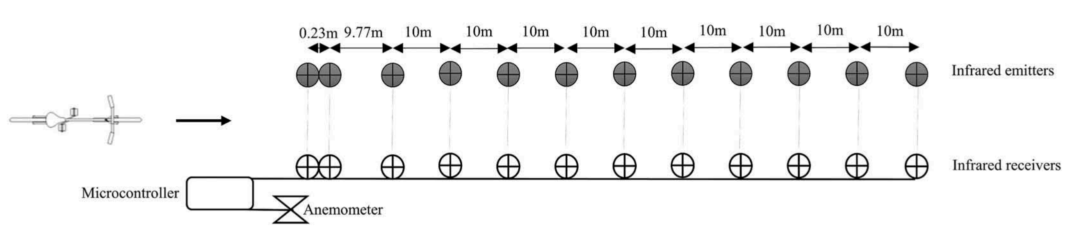

Figure 1. Illustration (top view) of coast-down test setup.

Table 1. Coast-down test location characteristics.

Date	Time	Location	Sample size	Bicycle volume*	Mean (range) of grade in %
Tu 6/28	11:30–15:00	UBC	10	not available	0.6 (0.4;1)
Th 6/30	11:30–15:00	UBC	12	not available	0.6 (0.4;1)
We 7/06	1:00–16:00	York Ave	22	2,475	−0.4 (−0.9;0.2)
We 7/13	12:00–16:30	Ontario North	48	5,464	−0.1 (−0.9;0.4)
Fr 7/15	12:30–17:00	Science World	20	3,985	0.2 (−0.6;0.9)
We 7/20	12:30–16:00	Ontario South	10	442	0.3 (−0.4;0.9)
Th 7/21	12:00–16:30	Union St	38	3,558	0.5 (−0.6;2.7)
Fr 7/22	12:00–16:00	Sunset Beach	38	1,650	−0.1 (−2.6;0.7)
Mo 7/25	14:30–17:00	North Arm Trail	11	229	0.3 (−0.9;0.8)
We 7/27	15:00–19:00	Ontario North	59	5,464	−0.1 (−0.9;0.4)
Fr 7/29	15:00–17:00	York Ave	29	2,475	−0.4 (−0.9:0.2)
Th 8/04	15:00–19:00	Union St	50	3,558	0.5 (−0.6;2.7)
Fr 8/05	14:30–18:00	Expo Blvd	34	1,379	0.6 (0.1;1.6)
We 8/10	16:00–19:00	Expo Blvd	19	1,379	0.6 (0.1;1.6)
Th 8/11	15:00–19:00	Sunset Beach	44	1,650	−0.1 (−2.6;0.7)
Fr 8/12	15:00–18::30	Science World	45	3,985	0.2 (−0.6;0.9)
Tu 8/16	14:30–17:00	North Arm Trail	10	229	0.3 (−0.9;0.8)
We 8/17	12:30–16:00	Ontario North	58	5,464	−0.1 (−0.9;0.4)

* Bi-directional summer weekday average in 2012 (El Esawey, Lim, & Sayed, 2015).

during cycling. Bicycles were weighed with any attached cargo due to participant reluctance to remove cargo in pilot testing. Other bags carried by the cyclist (e.g., backpacks) were weighed separately as cargo. Participant weight and height were used to calculate Body Mass Index (BMI) as $mass/height^2$; the mass used in this calculation included the cyclist's clothes.

Participants were next instructed in performance of the coast-down test as follows:

(1) Accelerate up to a conformable, typical riding speed by the chalk-marked "stop pedalling line";
(2) Coast, without pedalling or braking, along a dashed line chalk-marked every few meters throughout the coasting field;
(3) Stop in case coasting speed becomes too low to proceed safely, or upon reaching the chalk-marked "end line".

Each intercepted cyclist performed the coast-down test once, although participants who braked, pedalled, swerved, or had some other observed violation of the test protocol were asked to re-perform the test. No specific instruction was given about leg position. Bicycles were tested in the condition at which they arrived, without any maintenance evaluation or repair.

Data analysis

All data analysis was performed using the statistical software R, version 3.3.0 (R Core Team, 2016). Resistance parameters were fit using the genetic algorithm R package "GA" (Scrucca, 2013). Resistance parameters are positive by definition, finitely bounded and expected to be positively skewed (confirmed in results below), so measured values were fit to Weibull and Gamma distributions using Maximum Likelihood estimation with the "fitdistrplus" R package (Delignette-Muller & Dutang, 2015). Selection of the best-fit distribution was based on visual inspection and five statistical tests: Kolmogorov-Smirnov (K-S), Cramer-von Mises, Anderson-Darling, Aikake's Information Criterion and Bayesian Information Criterion. Non-parametric K-S tests were used to test for differences between resistance parameters across categorical sub-sets of the sample significant at $p<0.05$. Pearson's correlation coefficient was used to measure linear relationships between continuous parameters significant at $p<0.05$. Measured distributions are presented below as boxplots where the central line is the median, the box gives the interquartile range (IQR, 25^{th}-75^{th} percentile), whiskers give the range of observations up to $1.5 \times$ IQR, and circles indicate outlier observations beyond the whisker range.

Of 648 cyclists who gave consent to participate in the study, resistance parameters were successfully estimated for 557. Of the other 91 participants, 3 reported insufficient time to complete the test, 13 tests failed because of instrumentation issues (sensor power loss), 11 tests had an insufficient coasting length (<50m), and 64 tests yielded poor parameter fitting results (sum of square error over 1 second). Poor fit results could have been due to unobserved violations of testing protocols (braking, swerving, etc.). Wind was not an issue for any of the tests because of high initial bicycle speeds (average 6.4 m/s, standard deviation 1.1 m/s) and relatively low-wind days (average wind speed 1.3 m/s, standard deviation 1.2 m/s). Apparent wind was within ±45° of the direction of travel for all tests; low apparent wind angles were found to yield the most precise estimates in validation testing because of the stability of the apparent wind direction as the cyclist slows (Tengattini & Bigazzi, In press).

Results

Figure 2 summarises age and sex for the sample. Of the 557 participants, 348 were male, 188 were female, and 21 preferred not to state their sex. The average participant age was 40 (standard deviation 15, range 6–80). Table 2 gives age and sex for the sample and for cyclists in the Vancouver metropolitan area based on a 2011 household travel survey (TransLink, 2013). The sample is qualitatively representative of the broader survey data, but with more females and slightly older (chi-squared tests significant at $p<0.05$).

Summary statistics for measured physical characteristics are given in Table 3 (sample sizes vary because not all participants consented to all questions or measurements). Figure 3 shows the distributions of participant and bicycle masses and Figure 4 shows the distributions of resistance parameters by sex. Bicycles with

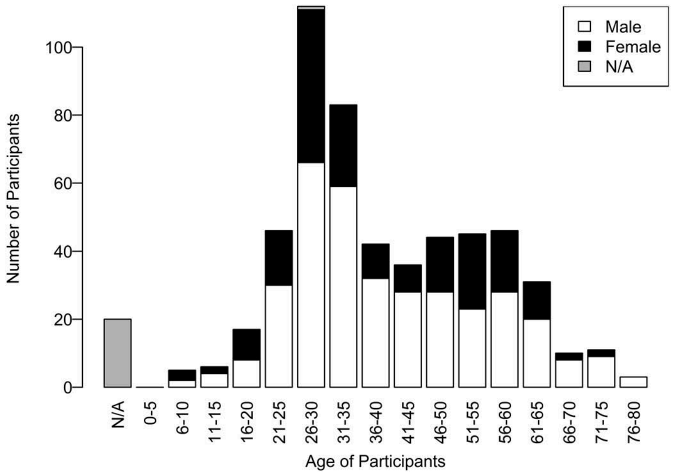

Figure 2. Participants by age (in years) and sex; N/A – Not Available.

Table 2. Age and sex in the study sample versus cyclists in a regional household travel survey.

P	Range [-]	Metro Vancouver, 2011* [%]	This Study [%]
Age (years)	5–12	8	1.5
	13–17	8	1.2
	18–24	5	8.8
	25–44	47	51.2
	45–64	28	30.2
	65–79	3	5.0
	80+	0	0.2
	Missing	-	2.0
Sex	Male	71	62.0
	Female	29	35.7
	Missing/Other	-	2.3

*(TransLink, 2013)

cargo were on average 4.6 kg heavier than bicycles without cargo. The average (standard deviation) of cyclist and cyclist + bike + cargo masses were 74.7 (15.4) and 92.2 (16.2) kg, respectively. The average (standard deviation) of BMI was 24.4 (3.8). Mean C_r was 0.0077 (95% Confidence Interval ±0.0003) with a standard deviation of 0.0036. Mean C_dA_f was 0.559 m^2 (95% Confidence Interval ±0.014 m^2) with a standard deviation of 0.170 m^2.

Resistance parameters were positively skewed (moment coefficient of skewness of 0.47 for C_r and 0.58 for C_dA_f). Measured C_r values were best approximated by a Weibull distribution (shape and scale parameters $k = 2.28$, $\lambda = 0.00874$), while C_dA_f values were best approximated by a Gamma distribution (shape and rate parameters $\alpha = 10.99$ and $\beta = 19.68$) – see Figure 5.

Measured resistance parameters and masses segmented by categorical variables are given in Table 4. Most cyclists rode in "tops" position (typical for flat handlebars); "drops" is the typical aerodynamic position, and "hoods" is a position in between the two. Fewer cyclists wore sport clothing (i.e. tight cycling shorts and jersey) than those who wore casual clothing. About half the participants had "commuter" tires, with a medium texture compared to smooth "slick" tires and "knobby" treaded tires.

Table 4 includes K-S test results for differences in C_r, C_dA_f and m by category (significant at $p<0.05$). Participants riding in tops position, with knobby tires, and wearing casual clothing had higher resistance parameters. Cyclists in casual clothing also had higher overall mass. E-bikes had higher overall mass and C_dA_f. Resistance parameters were not different by sex. Presence of a helmet (for 79% of participants, not included in Table 4) was not associated with any differences in C_r, C_dA_f, or m.

Figure 6 shows correlations among continuous variable characteristics (significant at $p < 0.05$). The highest correlations are for front/back tire pressures and widths, and tire pressures and widths are themselves negatively correlated. Rider age is positively correlated with mass and BMI. Rolling resistance coefficient is positively correlated with tire width and overall mass (including cargo), and negatively correlated with tire pressure. Effective frontal area is positively correlated with tire width, overall mass, age, and BMI, and negatively correlated with tire pressure. No correlation was found between C_r and C_dA_f.

Discussion

The results in this study show that real-world urban cyclists have a wide range of physical characteristics. Two published sources suggest approximate resistance values for a range of bicycles, measured with different techniques, but no known study reports systematic measurements from a sample of real-world in-use bicycles. Gross et al. (1983) report ranges for C_r of 0.003–0.014 and for C_dA_f of 0.31–0.56 m^2 for on-road "standard bicycles". They also report $C_r = 0.003$ and $C_dA_f = 0.31$ m^2 for "racing bicycles" and $C_r = 0.006$ and $C_dA_f = 0.56$ m^2 for "upright commuter" bicycles. Wilson (2004) reports ranges for C_r of 0.002–0.010 (on smooth surfaces)

Table 3. Physical characteristics sample statistics.

Parameter	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Mean	Standard deviation	N
Cyclists+Bicycle+Cargo Mass [kg]	35.4	82.0	90.9	100.9	154.7	92.2	16.2	552
Bicycle+Cargo Mass[kg]	7.3	16.0	18.0	20.0	40.7	18.3	4.1	423
Bicycle Mass [kg]	7.8	11.4	14.2	15.5	22.0	13.7	3.3	118
Cyclist Mass [kg]	21.9	65.0	73.5	83.0	139.0	74.7	15.4	552
BMI [kg/m^2]	15.8	22.0	23.8	26.3	45.0	24.4	3.8	513
C_r [-]	0.0012	0.0049	0.0076	0.0100	0.0189	0.0077	0.0036	557
C_dA_f [m^2]	0.209	0.434	0.539	0.655	1.128	0.559	0.170	557
Front Tire Pressure [kPa]	55	234	317	431	872	347	154	553
Back Tire Pressure [kPa]	48	234	317	445	876	352	157	553
Front Tire Width [cm]	2.0	2.8	3.3	4.2	9.6	3.5	0.9	553
Back Tire Width [cm]	2.0	2.8	3.3	4.2	9.6	3.5	0.9	553
Bicycle Year [-]	1945	2005	2009	2014	2016	2006	10	505
Bicycle Gears [-]	1	14	21	24	30	19	8	502

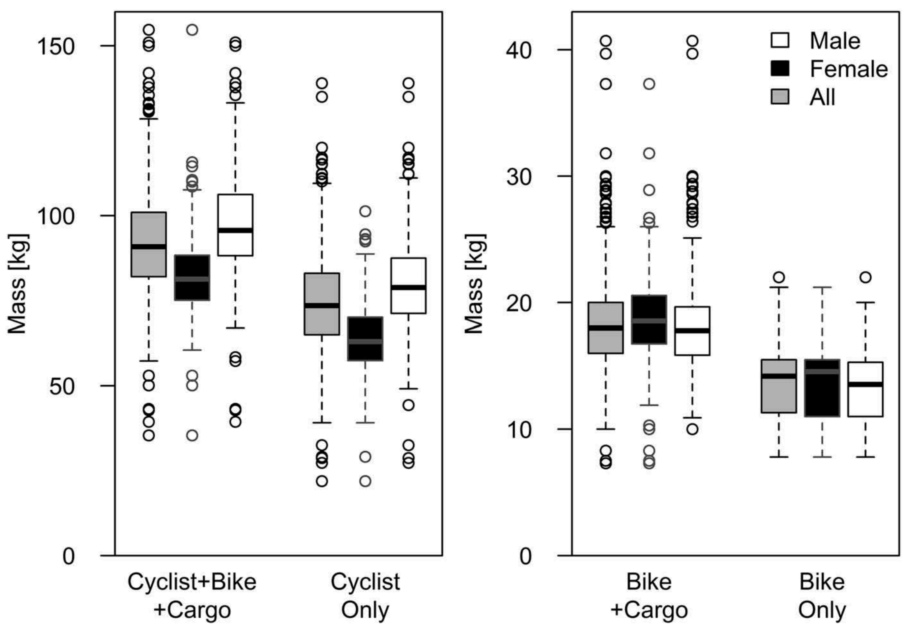

Figure 3. Participant, bicycle, and cargo mass by sex (central line gives the median, box gives the IQR, whiskers give the range up to 1.5 × IQR, and circles are observations outside the whisker range).

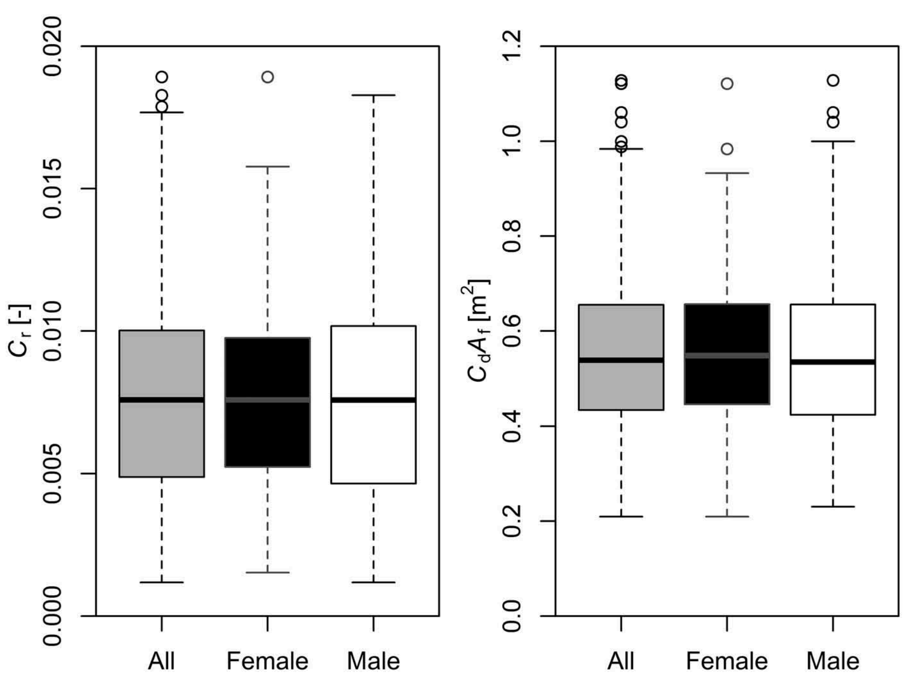

Figure 4. Rolling and Drag resistance parameters by sex (central line gives the median, box gives the IQR, whiskers give the range up to 1.5 × IQR, and circles are observations outside the whisker range).

and for C_dA_f of 0.04–0.63 m^2 (bicycles ranging from recumbents to upright commuters), as well as $C_r = 0.006$ and $C_dA_f = 0.63$ m^2 for a typical upright cyclist.

The mean C_r in this study, 0.008, is higher than the suggested value for "commuters" of 0.006 in both Gross et al. (1983) and Wilson (2004). The mean C_dA_f, 0.56, is the same as the suggested value for "commuters" in Gross et al. (1983) and lower than that in Wilson (2004), 0.63. The IQR of C_r (0.005–0.010) is within the ranges suggested by both Gross et al. (1983) and Wilson (2004), while the IQR of (0.43–0.66) is higher than both suggested ranges. Including the highest and lowest quartiles of measured resistance parameter values yields wider ranges than previously suggested, especially on the upper end of values.

Statistical tests support the hypothesis that resistance parameters are associated with attributes of the rider and bicycle. More specifically, cyclists with less sport-oriented attributes such as non-road bicycles, upright riding position, casual clothing, and larger, knobbier, and lower-pressure tires have higher resistance parameters. Tire pressure is negatively correlated with, while tire width and knobby tire type are

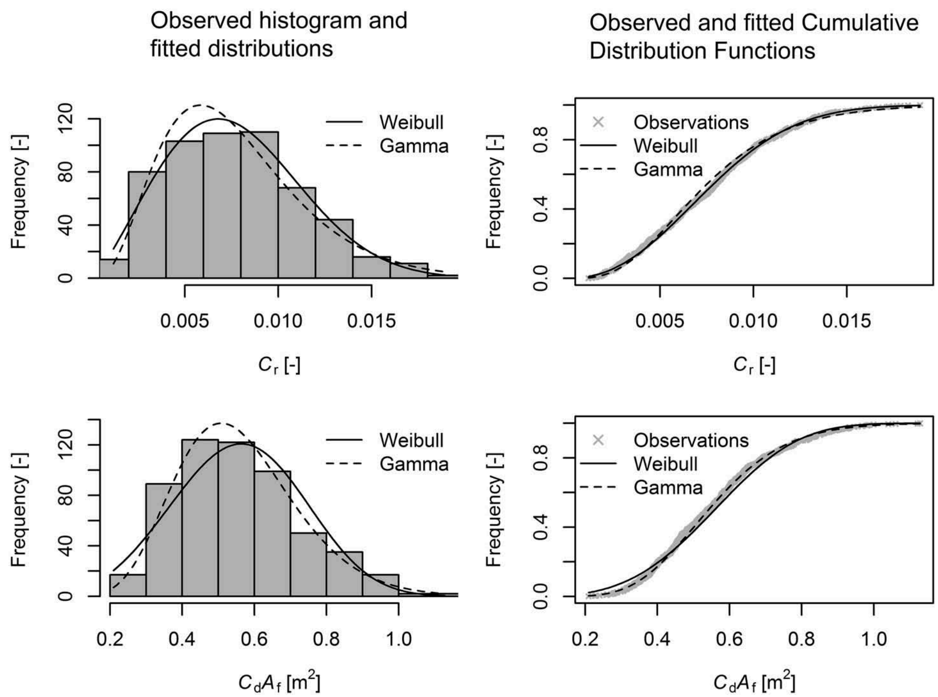

Figure 5. Resistance parameter observed and fitted distributions.

positively associated with C_r, consistent with other research (Bertucci et al., 2013; Macdermid et al., 2015; Wilson, 2004). More upright riding position, casual clothing, and BMI are positively associated with C_dA_f, also consistent with existing literature (Burke, 2003; Candau et al., 1999; Debraux et al., 2011; García-López et al., 2008; Wilson, 2004). Some relationships between physical attributes and resistance parameters are likely due to bicycle type differences – particularly for riding position and tire type. For example, upright riding positions are associated with higher C_r, likely due to larger, knobbier, lower-pressure tires on mountain-style bicycles (Bertucci et al., 2013; Macdermid et al., 2015), and inversely, wide, knobby, and low-pressure tires are associated with higher C_dA_f, likely due to more upright riding positions.

The observed systematic differences in resistance parameters indicate the importance of assessing a realistic distribution of travellers when estimating the exercise and travel performance of urban cycling. Large portions of the intercepted cyclists in this study were on non-road bicycles (60%) and wearing casual clothing (86%) – attributes which were associated with higher resistance parameters than typical sport road cyclists. An assumption of lower resistance parameter values would lead to under-estimates of cyclist power and energy, and over-estimates of cyclist speeds, which could be non-conservative in many applications. For example, the differences in average resistance parameters between cyclists with sport and casual clothing in this study (see Table 4) leads to a 22% difference in estimated cyclist power at 15 km/hr from Equation (1) for a level road with $m = 92$ kg and $\rho = 1.2$ kg/m^3. Physical characteristics of professional and competitive cyclists are relevant for modelling sport outcomes, but would serve poorly in estimates of exercise and travel outcomes related to active urban travel, such as bicycle commuting.

A limitation of this study is the precision of the field coast-down test for measuring resistance parameters. In a previous validation study (Tengattini & Bigazzi, In press), measurement error for the field test was up to a standard deviation of 0.001 for C_r and 0.1 for C_dA_f. Assuming the measurement error is random, it would inflate the variance in the sample values additively. Reducing the observed variance of 1.3x10^{-5} for C_r by a measurement variance of 10^{-6} yields a lower estimated variance of 1.2x10^{-5} (corresponding to a reduction in standard deviation of C_r from 0.0036 to 0.0035). Similarly, reducing the observed variance of 0.029 for C_dA_f by a measurement variance of 0.01 yields a lower estimated variance of 0.019 (corresponding to a reduction in standard deviation of from 0.17 to 0.14). After this adjustment, the ranges of resistance parameter values for the sample (mean ±2 standard deviations) become 0.001–0.015 for C_r and 0.28–0.83 for C_dA_f, which is still wider than the suggested ranges in both Gross et al. (1983) and Wilson (2004) discussed above.

Other limitations also stem from the challenges of collecting data from a large representative sample of intercepted urban cyclists. A key goal was minimizing participant burden to reduce the likelihood of sample bias toward more avid cyclists. For this reason, the coast-down test was performed once by each participant, although repeated testing could provide more precise estimates. Participants could not feasibly be asked to undress, and so BMI was calculated from their clothed weight. Reported BMI is thus not directly comparable to other values, but is still useful as an indicator of body size that can affect aerodynamic drag. Cyclists were allowed to coast in whatever pedal position they found comfortable, and most chose a position parallel to the ground. Backward pedalling could provide a more realistic measure of drag, but was a challenge for some inexperienced cyclists in pilot testing. To measure realistic resistance, bicycles were tested in their in-use maintenance condition, and some could have had mechanical issues such as dirty bearings or rubbing

Table 4. Measured resistance parameters and masses, segmented by categorical variables*.

Parameters	Category I	Category II	Category III	Category IV	Category V	
Sex	Male [348]	Female [188]				NA [21]
C_r [-]	0.0077 (0.0038)	0.0077 (0.0033)				
C_dA_f [m^2]	0.559 (0.175)	0.560 (0.161)				
Cyclist+Bike+Cargo Mass [kg]	97.7 (15.4)	82.1^{I} (13.2)				
Cyclist Mass [kg]	80.5 (14.3)	63.9^{I} (11.5)				
Riding Position	Drops [22]	Hoods [90]	Tops [438]			NA [7]
C_r [-]	0.0056 (0.0032)	0.0061 (0.0029)	$0.0081^{I,II}$ (0.0036)			
C_dA_f [m^2]	0.463 (0.130)	0.477 (0.122)	$0.579^{I,II}$ (0.173)			
Cyclist+Bike+Cargo Mass [kg]	92.9 (13.8)	89.8 (14.6)	92.5 (16.6)			
Cyclist Mass [kg]	76.8 (12.8)	75.3 (13.3)	74.5 (16.3)			
Cyclist Apparel	Sport [78]	Casual [477]				NA [2]
C_r [-]	0.0063 (0.0032)	0.0079^{I} (0.0036)				
C_dA_f [m^2]	0.486 (0.145)	0.570^{I} (0.170)				
Cyclist+Bike+Cargo Mass [kg]	87.5 (13.9)	92.9^{I} (16.4)				
Cyclist Mass [kg]	72.6 (13.0)	75.1 (16.1)				
Tire type	Slick [137]	Commuter [273]	Knobby [138]			NA [9]
C_r [-]	0.0070 (0.0035)	0.0074 (0.0033)	$0.0092^{I,II}$ (0.0039)			
C_dA_f [m^2]	0.498 (0.148)	0.579^{I} (0.172)	0.576^{I} (0.174)			
Cyclist+Bike+Cargo Mass [kg]	89.9 (14.7)	93.3 (15.6)	92.3 (18.5)			
Cyclist Mass [kg]	75.1 (13.9)	75.3 (15.4)	73.9 (18.0)			
Bicycle type	Road [225]	Hybrid [181]	Mountain [90]	Cruiser [37]	e-bike [7]	NA [17]
C_r [-]	0.0070 (0.0034)	0.0079^{I} (0.0035)	$0.0089^{I,II}$ (0.0041)	0.0078 (0.0039)	0.0103 (0.0042)	
C_dA_f [m^2]	0.505 (0.135)	0.579^{I} (0.176)	0.603^{I} (0.187)	0.640^{I} (0.179)	0.614^{I} (0.210)	
Cyclist+Bike+Cargo Mass [kg]	91.5 (14.5)	91.1 (15.9)	93.3 (18.3)	93.7 (16.0)	$106.3^{I,II,III}$ (11.0)	
Cyclist Mass [kg]	75.8 (13.9)	73.5 (16.4)	75.1 (17.8)	74.0 (16.1)	74.2 (9.5)	

* mean (standard deviation) and [sample size]; Roman numeral superscripts indicate the comparison categories for which a difference was found (significant at $p<0.05$) based on two-sample, two-sided, Kolmogorov-Smirnov tests

brakes. Thus, the reported C_r and C_dA_f do not strictly capture only rolling and drag resistances. In the coast-down equations, these parameters represent zero-order and second-order resistance forces more generally, and so are most appropriately applied in a two-factor power model such as Equation (1) (Tengattini & Bigazzi, In press).

This study characterised cyclists in Vancouver, Canada during summer and results may not be applicable in other contexts. Cities with substantially different bicycle mode shares would likely have different populations of cyclists. For example, cities with less utilitarian bicycle travellers would likely have lower distributions of resistance parameter values due to a higher proportion of sport cyclists. In addition, other countries might have substantially different bicycle fleets, such as more cruiser-style bicycles in Northern Europe or more mountain bicycles in South America, both of which would have higher resistance parameters. Major studies using cyclist physical parameters in other locations are encouraged to perform similar testing to determine the attributes of the sample or population of interest.

Conclusion

The results in this paper can improve understanding of bicycle performance for a realistic range of urban travellers. The main physical parameters in this study, C_r, C_dA_f, and m, can be used in bicycle speed, power and energy models, applicable to exercise performance, infrastructure design, travel behaviour modelling, health and safety assessments, and more. Furthermore, the reported parameter distributions can be applied in probabilistic designs and stochastic models. Simulations could sample from

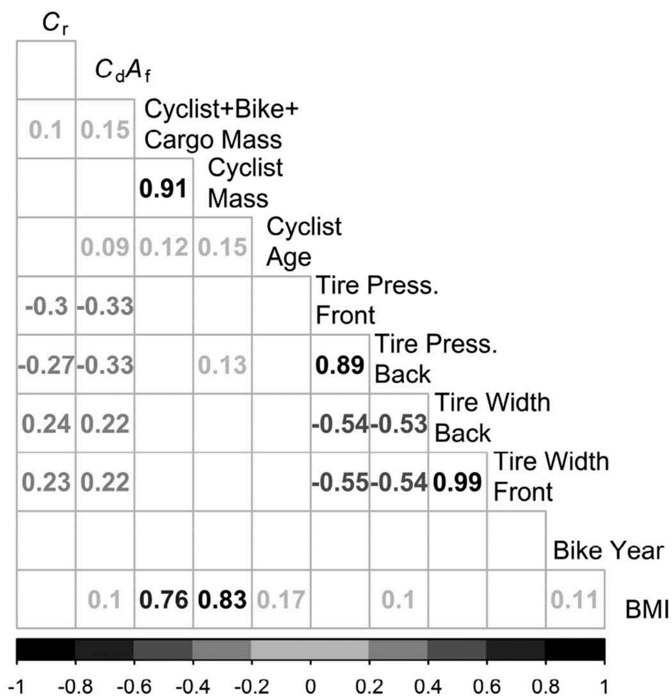

Figure 6. Correlation matrix (Pearson's linear correlation) of measured physical characteristics. Values shown are different from zero at a significance of $p<0.05$.

these distributions to generate synthetic travellers with realistic ranges of physical characteristics. The statistical comparisons above provide insights that could be used to select context-sensitive values for assumed cyclist parameters.

Future work will investigate relationships between physical characteristics and other travel and traveller attributes, such as socio-demographics and trip type, to provide further information to generalise to other populations. In addition, relationships between resistances and travel preferences (mode, route, speed) could reveal systematic differences relevant to network and infrastructure design. Other future work should conduct similar intercept studies in other locations for cross-city comparisons of typical urban cyclist physical characteristics.

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