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Speed and road grade dynamics of urban trips on electric and conventional bicycles

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ABSTRACT

Electric-assist bicycles (e-bikes) allow cyclists to travel at higher speeds and climb hills with less effort. Beyond average speed differences, little is known about the unique travel dynamics of e-bikes. The objective of this study is to examine systematic differences in speed and road grade dynamics between electric and conventional bicycle trips. Data were collected for 1451 utilitarian bicycle trips in Vancouver, Canada (10% on e-bikes). A subset of conventional bicycle trips were matched to the age, gender, purpose, and terrain characteristics of the e-bike sample. Biking schedules were constructed to represent the archetypal speed and grade dynamics of each set of trips. Results show that in addition to higher speeds, e-bike trips have significantly greater speed dynamics, substantially increasing the motive power and energy required for e-bike travel. Speed and grade dynamics are important aspects of microscopic cycling behaviour, with applications including vehicle design, facility design, and health evaluation.

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1. Introduction

Many cities and countries are promoting cycling through polices, programmes and infrastructure, motivated by goals related to public health, air quality, climate change, traffic congestion, and more (Pucher and Buehler 2012). The physical effort required to travel by bicycle (and related considerations such as perspiration) is a barrier to wider adoption of cycling for transportation (Winters et al. 2011). Electric-assist bicycles (e-bikes) provide a means to reduce the physical demands of cycling on the rider (MacArthur and Kobel 2014; Rose 2012). E-bikes allow riders to travel at higher speeds and climb hills with less effort by providing additional propelling force through a motor drawing electrical energy from an on-board battery. Existing e-bikes are available to travellers in a range of styles and designs, ranging from vehicles very similar to conventional bicycles to what are essentially electric scooters.

E-bike use has steadily increased over the past decade, although the overall adoption is still fairly low in most countries and there is wide disparity in use around the world (Fishman and Cherry 2016). Some outstanding research questions about e-bike adoption and use include safety impacts (Langford, Chen, and Cherry 2015; Schepers et al. 2014), net environmental impacts (Cherry, Weinert, and Xinmiao 2009), impacts on physical activity and consequent health outcomes (Gojanovic et al. 2011; Langford et al. 2017), and impacts on traffic flow (Jiang et al. 2017; Zhang, Ren, and Yang 2013). Several studies have reported differences in ridership and trip purposes between electric and conventional

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bicycles. E-bike ridership in North America has been reported as being disproportionately older and with physical limitations (MacArthur, Dill, and Person 2014; Wolf and Seebauer 2014). E-bikes in the United States are used proportionately more for utilitarian trips (work and errands) than conventional bicycles (Ling et al. 2017). Other evidence suggests e-bikes are used for longer trips than conventional bicycles (Fyhri and Fearnley 2015).

On a microscale (sub-trip) level, e-bike riders typically travel faster than riders on conventional bicycles. Langford, Chen, and Cherry (2015) reported that in the United States the average on-road speed of e-bikes was higher than conventional bicycles, whereas conventional bicycles travelled faster on shared paths. Lin et al. (2008) reported that the mean operating speed of e-bikes in China was 22 km/h: 7 km/h faster than conventional bicycles. In a separate study in China, e-bikes were reported to travel at 13.0 and 11.9 km/h on average in Shanghai and Kunming, respectively, and conventional bicycles in the same cities to travel at 11.4 and 10.5 km/h on average (Cherry and Cervero 2007). Other recent studies reported average speed differences of 2–9 km/h between electric and conventional bicycles (Baptista et al. 2015; Schleinitz et al. 2017), with one study modelling average speed differences as a function of road grade on individual segments, ranging from no difference on steep descents to e-bikes 3 km/h faster on steep ascents (Flügel et al. 2017).

Beyond average speed differences, there has been little investigation of the unique microscopic travel dynamics of e-bikes, and how they may differ from conventional bicycles. Speed dynamics (positive and negative acceleration), grade dynamics, and the interaction between the two are likely to be different between electric and conventional bicycles, assuming riders change their travel behaviour in response to the availability of motor power. Riders may choose to accelerate faster, to maintain a higher speed on ascents, or to take a hillier route, for example, if the perceived costs of acceleration, power, and ascents are lower (Bigazzi and Lindsey 2019). Such differences in travel dynamics would have impacts on safety, energy expenditure and physical activity, breathing rates and pollution inhalation, vehicle performance (e.g. battery range), and traffic flow. Hence, an understanding of the unique speed and grade dynamics of e-bikes is essential for applications such as safety and health evaluation, traffic flow modelling, e-bike vehicle design, and facility design.

The objective of this study is to examine systematic differences in speed and road grade dynamics between electric and non-electric (conventional) bicycle trips. It is hypothesized that because of the power available from the motor, e-bike riders exhibit more dynamic speeds with greater acceleration activity. 'Biking schedules' (archetypal riding patterns) are generated from naturalistic travel data and compared for electric and conventional bicycles. Biking schedules are a recently-developed method for characterizing and analyzing microscale bicycle travel characteristics (Mohamed and Bigazzi 2018). Impacts on cycling power and energy are also evaluated.

2. Methods

2.1. Data

2.1.1. Data collection

A large dataset of naturalistic bicycle trips was collected in Vancouver, Canada. Recruitment and data collection occurred June through October, 2017. Eligible participants were people of age 14 or over who 'typically cycle at least once a week in Metro-Vancouver'. Potential participants were first directed to a website where informed consent was obtained. Then, they completed an approximately 10-minute long questionnaire to collect cycling experience, travel habit, and socio-demographic information. Finally participants were asked to record all of their active travel activity (walking, running, cycling, etc.) for a 7-day period, beginning on a date of their choosing, which was instructed to be a 'typical week when [they] are not travelling out of town'. Only the cycling trips were used in this analysis.

The smartphone application 'Ride with GPS' was recommended to participants for recording their trips. This application was selected after a review of options because it was available on both Android and iOS platforms, provided 1 Hz logging of travel data (GPS and heart rate) and enabled direct sharing of recorded data with the research team through a 'friends' feature (reducing respondent burden). Participants were instructed to configure the application to record at 1-second intervals, and were asked to label each trip within the application with travel mode (walk, run, bike, e-bike, other) and purpose (work, school, errand, leisure, exercise, other). Participants could also record and share their trips using any device or application they preferred by sending the researchers their recorded data, and were offered a smartphone to use during the week if they did not own or chose not to use a personal smartphone. Participants received daily reminders by email during their selected data collection week, and were instructed to identify any 'missed trips' which were not recorded that day. All participants were entered into a draw for 20 gift cards of CA$25 each. Participants who also provided heart rate data (not included in this analysis) were further incentivized with custom cycling hats or socks.

Approval was obtained from the University of British Columbia Research Ethics Board before recruitment began. Recruitment was carried out via print flyers at bicycle shops, invitation cards distributed directly to cyclists at bicycle facilities in the region, social media posts, and emails to cycling groups and organizations within the region and to participants in a previous cycling study. E-bike groups and e-bike shops were targeted in an attempt to over-sample this small sub-population of cyclists.

2.1.2. Data processing

GPS data recorded by the smartphone application were obtained in 'tcx' format. Each observation was comprised of a single GPS reading at 1-second intervals with time stamp, longitude, latitude, altitude, and heart rate (if recorded) information. Observations with duplicate time stamps within the same file were corrected or removed at the beginning of the data cleaning process. Several participants recorded more than one trip in the same file by keeping the application running. Distinct trips within the same file were separated by stops longer than five minutes at a single location; these stops were identified by computing periods in which the cumulative speed-based distance was more than three times the actual net moved distance, based on past research (Cich et al. 2016; Fu et al. 2016). After cleaning, only bicycle trips with an average speed higher than 5 km/h and a total duration longer than 1 min were retained.

The GPS-based altitude data were determined to be unreliable due to issues such as multipath effects, atmospheric layers, and obstruction (Menard et al. 2011). Road grades were derived by extracting elevation data from a Digital Elevation Model (DEM), as is common practice (Casello and Usyukov 2014; Strauss and Miranda-Moreno 2017). Elevation data for each observation were extracted from the Canadian Digital Surface Model, with a horizontal resolution of approximately 20 m (Natural Resources Canada 2015). Road grade was calculated as the difference in elevation divided by the travelled distance between each pair of consecutive observations. Road grade values were capped at $\pm$10% to eliminate erroneously steep grade estimates due to cycling on elevated structures (which are not in the DEM) or cycling parallel to steep terrain within the resolution of the DEM or the precision of the GPS.

Raw speed was calculated as the ratio of the moved distance to the time interval between each pair of non-missing consecutive observations. Missing speeds were then linearly interpolated between non-missing speeds up to five seconds apart. Longer gaps were left as missing data. Speed and grade were then smoothed using kernel smoothing with a bandwidth of 10 observations. Various bandwidths and other smoothing algorithms (such as moving average, spline smoothing, local polynomial regression, and Savitzky–Golay) were also examined, and the kernel approach was selected because it conserved zero-speed observations and provided realistic speed and grade differentials. The best speed and grade processing algorithms to apply to smartphone-based GPS data for cycling activity is an area requiring further research. Acceleration was calculated for each pair of non-missing consecutive speed observations as the difference in smoothed speeds.

2.2. Biking schedule construction

Biking schedules are high-resolution speed-grade profiles that represent archetypal cycling patterns. The recently-introduced concept and techniques of biking schedules (Mohamed and Bigazzi 2018) are derived from driving schedules (also known as driving cycles), which were developed and used to represent typical driving behaviour for motor vehicle energy and emissions measurement and modelling (Tong and Hung 2010). The main differences are that biking schedules include road grade (because of the relationships between cycling speed and road grade) and use a different set of cycling-relevant assessment parameters.

The biking schedule construction methodology can be summarized as follows; for further details see Mohamed and Bigazzi (2018). First, a set of 'target' assessment parameters are calculated that summarize the aggregate characteristics of a naturalistic travel data set with speed, acceleration, and road grade information. The 12 assessment parameters are given in Table 1. Biking schedules are ultimately evaluated based on the Performance Value (PV): the weighted percent difference between the assessment parameters of the biking schedule and the target assessment parameters. The performance value for each individual assessment parameter is the absolute percent difference between the schedule and target parameter values, with the exception of the speed-acceleration-grade probability distribution (SAGPD) for which it is the root mean square error (RMSE) between the schedule and target percentage time in each cell of the array. The overall PV is the weighted average of individual parameter performance values, with weights distributed equally among four sets of parameters that represent speed (1/16th each on ATS, AMS, PTI, PTC), acceleration (1/16th each on AAA, PTA, PTD, APW), grade (1/12th each on AAG, PTPG, PTNG), and all three dimensions (1/4th on SAGPD). A lower PV means that the schedule is closer to the target parameters and more representative of the observed trip data.

The 'best incremental' method from Mohamed and Bigazzi (2018) is used to create candidate biking schedules, based on good performance and moderate processing time with a large, high-resolution GPS dataset. The travel data are first segmented into 'microtrips' of 150 m. This microtrip length definition was selected based on an initial exploration of several possible microtrip definitions described in the Supplementary Material. The extracted microtrips are then clustered by average speed, average acceleration, and average grade using a K-means clustering algorithm. The number of clusters (in this study 15) is determined by adding clusters sequentially until the reduction in the sum of squared errors within clusters is less than 10%.

An initial microtrip is randomly selected from the subset of trip-starting microtrips to initiate a candidate biking schedule. A stochastic Markov chain process is then applied to generate a sequence of

Table 1. Assessment parameters.

Parameter	Definition	Units
ATS	Average trip speed	km/h
AMS	Average moving speed (speed $>$ 0)	km/h
PTI	Percent time idling (speed $=$ 0)	%
PTC	Percent time cruising (speed $>$ 1 km/h and acceleration between -0.1 and 0.1 km/h/sec)	%
AAA	Average absolute acceleration	km/h/sec
PTA	Percent time accelerating ($>$ 0.1 km/h/sec)	%
PTD	Percent time decelerating ($<$ -0.1 km/h/sec)	%
APW	Average positive work per distance[a]	m/sec^2
AAG	Average absolute grade	%
PTPG	Percent time positive grade ($>$ 0.5%)	%
PTNG	Percent time negative grade ($<$ -0.5%)	%
SAGPD	Speed-acceleration-grade probability distribution[b]	%

[a] sum of differences between successive squared speeds with positive acceleration, divided by the travel distance.

[b] percent time in each cell of a three-dimensional speed-acceleration-grade distribution array with speed intervals of 5 km/h, acceleration intervals of 0.2 km/h/sec, and grade intervals of 1%.

clusters starting from the cluster of the initial microtrip. For each successive cluster in the chain, the microtrips in that cluster are filtered based on continuity criteria: beginning within 1 km/h speed and 1% grade of the end of the last microtrip in the schedule. Microtrips meeting the continuity criteria are provisionally added to the end of the existing schedule one at a time, a PV is calculated for each, and the microtrip generating the lowest-PV schedule is appended. This process is repeated for each successive cluster in the sequence until the desired candidate schedule length is reached (in this study 25 min). The final biking schedule is selected based on lowest PV from a set of 20 such generated candidate schedules (each starting from a different initial microtrip).

2.3. Matching samples

Because the context of e-bike trips is expected to be different from conventional bicycle trips, Propensity Score Matching (PSM) was used to identify a comparable set of conventional bicycle trips to match the smaller set of e-bike trips in the dataset. This approach was used to isolate the effects of the e-bike specifically, distinct from other systematic cycling differences related to socio-demographics, trip purpose, and terrain. The PSM method was implemented with the 'MatchIt' package in the statistical software R (Ho et al. 2011).

Several variables were considered for matching criteria including age, gender, home location, level of education, household income, terrain, and trip purpose. The matching was evaluated using chi-square tests with a 95% significance level. Only the following four combinations of variables matched on age, gender, trip purpose, and terrain yielded matched samples with no significant difference from the e-bike trips (i.e. *p*-values over 0.05):

(1) Matched on A-G: Age + Gender
(2) Matched on A-G-P: Age + Gender + Purpose
(3) Matched on A-G-T: Age + Gender + Terrain
(4) Matched on A-G-P-T: Age + Gender + Purpose + Terrain

Age and trip purpose were represented as six-level factors, gender as a binary variable, and terrain as the three assessment parameters related to road grade: average absolute grade (AAG), percentage time positive grade (PTPG), and percentage time negative grade (PTNG).

After matching, 6 sets of sample trips were defined: all e-bike trips, all conventional bicycle trips, and 4 subsets of conventional bicycle trips matched to the e-bike sample. Differences in cycling dynamics between these sets of trips were first examined by comparing the assessment parameters with *t*-tests. Then biking schedules were constructed and compared from the data in each set of trips.

The energy differences of the developed schedules were examined by estimating motive power from speed (v_i in m/s) and road grade (G_i unit-less) at each second of the schedule, using the equation in Bigazzi and Figliozzi (2015):

$$P_i = \max\{0, 0.5m(v_i - v_{i-1})^2 + 9.81mv_i(C_r + G_i) + 0.6C_dA_fv_i^3\}$$

The power calculation used previously-determined representative mass (m in kg) and resistance parameter (C_r unit-less and C_dA_f in m^2) values for cyclists in the region, given in Table 2 (Tengattini and Bigazzi 2018). Motive power was aggregated over time to calculate cumulative motive energy. Motive energy includes power from both the rider and motor (if present).

Table 2. Power equation parameters, from Tengattini and Bigazzi (2018).

Parameter	Conventional bicycles	Electric bicycles
Total mass of rider, bicycle, and cargo, m (kg)	90	106
Coefficient of rolling resistance, C_r (unit-less)	0.0079	0.0103
Effective frontal area, C_dA_f (m^2)	0.580	0.614

3. Results

3.1. Overview of sample

A total of 260 people participated in the study by completing the initial questionnaire, of which only 148 participants ultimately provided usable GPS data for their trips. 'Ride with GPS' was used by 131 of the final set of participants; the other 17 used other smartphone applications such as 'Strava' or other GPS devices (some did not report the device they used). Of the 2,109 downloaded files, 62 (3%) were corrupted or devoid of data. Participants also reported 129 missed trips. GPS location information was missing from 18% of the 1-second interval data (including stops); after processing, 8% of 1-second speed data were missing. Ultimately, GPS data were collected for 2,314 trips (70% bike, 8% e-bike, 14% walk, 2% run, and 7% unknown), with a total moved distance of 14,961 km over 875 h. There were 35 e-bike owners in the sample, of which 14 recorded e-bike trips during the data collection. Exercise trips (4%) and trips with less than 80% complete speed data were excluded, which left 1,308 conventional and 143 electric bicycle trips for further analysis.

The cyclist sample was 58% male, similar to the 62% observed in a recent cyclist intercept survey in the region (Tengattini and Bigazzi 2018), and lower than the 71% reported in the region's 2011 household travel survey (TransLink 2013). Figure 1 gives the income distribution of the sample compared with the two other samples of regional cyclists. Figure 2 gives the cumulative age distributions for the same three samples. Chi-square tests comparing the age and income distributions of the samples at $p < 0.05$ are both non-significant compared to the 2016 intercept survey and significant compared to the 2011 household travel survey.

3.2. Matched samples

Table 3 summarizes the six samples of bicycle trips: e-bike trips, unmatched conventional bicycle trips, and 4 subsets of conventional bicycle trips matched to the e-bike trips by PSM. The e-bike sample trips were made by older riders than the conventional bicycle trips, with a much larger share (67% versus 39%) over 40 years old and much smaller share (6% versus 35%) under 31 years old. The percent male is comparable for electric and conventional bicycle trips (64% versus 61%). E-bikes were more frequently used for work trips, and less frequently for school, errands, or other trips; the share of leisure trips was similar. The three terrain variables were also similar between the electric and conventional bicycle trip samples.

Table 4 gives the assessment parameters (mean and standard deviation) for each of the six samples. The SAGPD parameter is excluded because it does not have an interpretable single value. The table also indicates the results of two-tailed, two-sample t-tests (at $p < 0.05$) comparing the matched and

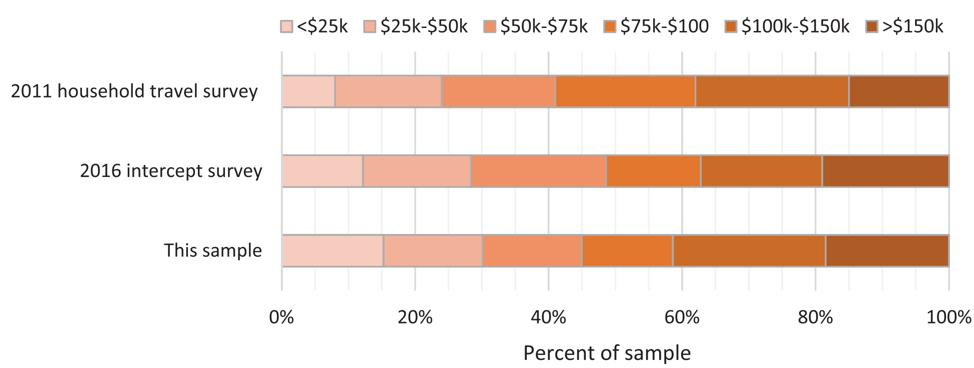

Figure 1. Income distributions of cyclist samples (in Canadian dollars).

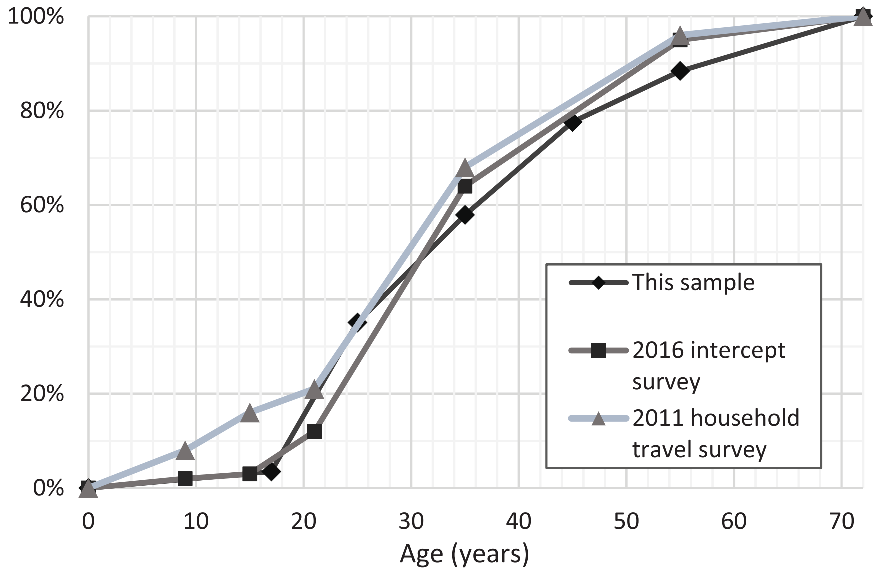

Figure 2. Cumulative age distributions of cyclist samples.

Table 3. Summary of trip samples.

	E-bike trips	Matched on A-G[a]	Matched on A-G-P	Matched on A-G-T	Matched on A-G-P-T	Unmatched conventional bicycle trips
Number of trips	143	143	143	143	143	1308
Age in years (% of sample trips)						
< 20	0.0	0.0	0.0	0.0	0.0	2.3
21–30	6.3	6.3	6.3	7.7	12.6	32.9
31–40	26.6	26.6	26.6	25.2	26.6	26.0
41–50	52.4	52.4	53.8	47.6	44.8	22.1
51–60	5.6	5.6	5.6	6.3	2.8	9.8
> 60	9.1	9.1	7.7	13.3	13.3	6.9
Percent male	64.3	64.3	70.6	56.6	64.3	60.7
Trip purpose (% of sample trips)						
Work	65.0	56.6	65.7	52.4	60.1	46.3
School	0.0	4.2	0.0	2.1	0.0	13.0
Errand	6.3	14.0	9.1	17.5	11.2	15.8
Leisure	11.9	15.4	7.7	18.2	11.2	11.3
Other	16.8	9.8	17.5	9.8	17.5	8.6
Missing	0.0	0.0	0.0	0.0	0.0	4.7
Terrain variables: mean (standard deviation) of trip values						
AAG	2.35 (0.85)	2.48 (0.71)	2.54 (0.60)	2.25 (0.79)	2.41 (0.85)	2.40 (0.67)
PTPG	41.7 (10.7)	44.6 (11.7)	45.7 (11.8)	41.5 (13.6)	40.9 (11.8)	44.4 (12.2)
PTNG	38.9 (10.4)	39.3 (12.0)	39.2 (10.9)	38.3 (12.0)	39.3 (11.4)	39.1 (11.4)

[a] A: Age, G: Gender, P: Trip purpose, T: Terrain.

e-bike sample trips (paired), and comparing all conventional bicycle trips with the matched and e-bike samples (unpaired).

Compared to all four matched samples, the e-bike trips had significantly higher average speeds (ATS, AMS), average absolute acceleration (AAA), percent time accelerating and decelerating (PTA, PTD) and average positive work (APW) at $p < 0.05$, and significantly lower percent time cruising (PTC). The terrain parameters were less consistent across matched samples, with no significant differences from the two samples matched on terrain (as expected), but significantly lower percent time positive

Table 4. Mean (standard deviation)[a] of assessment parameters for e-bike, conventional bicycle, and matched sample trips.

Parameter[b]	E-bike trips	Matched on A-G[c]	Matched on A-G-P	Matched on A-G-T	Matched on A-G-P-T	Unmatched conventional bicycle trips
ATS	21.7 (7.60) ^{C}	15.7 (4.53) ^{E,C}	16.7 (4.36) ^{E}	16.3 (5.23) ^{E}	15.9 (4.91) ^{E}	16.6 (4.62)
AMS	22.5 (7.33) ^{C}	16.4 (4.55) ^{E,C}	17.4 (4.34) ^{E}	16.9 (5.22) ^{E}	16.6 (4.90) ^{E}	17.3 (4.54)
PTI	4.28 (4.62)	4.13 (4.27)	3.94 (5.03)	3.96 (5.03)	4.21 (6.04)	3.71 (5.37)
PTC	14.5 (6.89) ^{C}	17.4 (7.87) ^{E}	17.3 (7.53) ^{E}	19.0 (8.30) ^{E}	18.1 (7.23) ^{E}	17.8 (7.30)
AAA	0.60 (0.20) ^{C}	0.47 (0.14) ^{E}	0.48 (0.15) ^{E}	0.44 (0.13) ^{E,C}	0.46 (0.13) ^{E}	0.46 (0.14)
PTA	39.2 (4.86) ^{C}	37.5 (4.93) ^{E}	37.4 (5.24) ^{E}	36.8 (5.02) ^{E}	37.4 (4.66) ^{E}	37.3 (5.04)
PTD	39.3 (4.51) ^{C}	37.3 (5.05) ^{E}	37.3 (5.19) ^{E}	35.9 (5.54) ^{E,C}	36.7 (5.60) ^{E}	37.4 (5.16)
APW	2.08 (0.69) ^{C}	1.72 (0.58) ^{E}	1.76 (0.58) ^{E}	1.58 (0.48) ^{E,C}	1.69 (0.51) ^{E}	1.69 (0.57)
AAG	2.35 (0.85)	2.48 (0.71)	2.54 (0.60) ^{E,C}	2.25 (0.79) ^{C}	2.41 (0.85)	2.40 (0.67)
PTPG	41.7 (10.7) ^{C}	44.6 (11.7) ^{E}	45.7 (11.8) ^{E}	41.5 (13.6) ^{C}	40.9 (11.8) ^{C}	44.4 (12.2)
PTNG	38.9 (10.4)	39.3 (12.0)	39.2 (10.9)	38.3 (12.0)	39.3 (11.4)	39.1 (11.4)

[a] ^{E} indicates $p < 0.05$ for two-tailed paired t-tests comparing matched versus e-bike sample trips ($N = 143$); ^{C} indicates $p < 0.05$ for two-tailed unpaired t-tests comparing e-bike and matched samples ($N = 143$) versus all conventional bicycle trips ($N = 1308$).
[b] Parameter definitions, including units, are in Table 1.
[c] A: Age, G: Gender, P: Trip purpose, T: Terrain.

grade (PTPG) than the two other samples, and significantly lower average absolute grade (AAG) than one of the matched samples (matched on age, gender, and purpose). Compared to the full conventional bicycle sample, the e-bike trips were again significantly faster (higher ATS, AMS), with greater absolute acceleration (AAA), greater positive work (APW), more time accelerating and decelerating (higher PTA, PTD), less time cruising (lower PTC), and less time on positive grades (lower PTPG). Percent time idling (PTI) and percent time negative grade (PTNG) were not significantly different between any of the samples.

The matched samples were also significantly different from the full set of conventional bicycle trips for some parameters, with significant differences indicating lower speeds, lower absolute acceleration, less time decelerating, lower positive work, less time on positive grades, and both larger and smaller absolute grades. Other than for terrain, these differences in speed and acceleration characteristics between the matched and full conventional bicycle samples are in the opposite direction of the differences between the e-bike sample and the full conventional bicycle sample.

3.3. Biking schedules

Table 5 gives the performance values for the six biking schedules generated from each of set of trips. The overall PV for all six schedules is under 3%, indicating that the biking schedules closely represent the speed, acceleration, and grade characteristics of the sample trips. The only parameter that deviated from the target value by more than 10% was percent time idling (PTI) for a single schedule. The PTI had high variability among trips; note that it is the only parameter with a standard deviation greater than the mean in Table 4. The six biking schedules are composed of 43–64 microtrips – the most for the e-bike schedule, because of the higher average speed.

All six biking schedules are provided in a data file in the Supplemental Material. Figure 3 illustrates three of the biking schedules for the e-bike trip sample, the subset of conventional bicycle trips matched on age, gender, trip purpose, and terrain, and all conventional bicycle trips. Both speed and grade exhibit large variability over the schedules, reflecting the dynamics of cycling on an urban street network in a moderately hilly city. The e-bike schedule reaches the highest speed (46 km/h), as expected. Average speeds range from 16 to 23 km/h, again highest for e-bike. The schedules include only a few full stops over the 25 min, consistent with the observed trip data in which around 4% of trip time was idling, on average. Road grades in the schedules range +/−9%, fluctuating between positive and negative grades 34–56 times (on average twice a minute). Average absolute grades are 2.1% to 2.7%; median absolute grades are lower at 1.4% to 2.1%. Speed and grade are negatively correlated in all six schedules, with Pearson correlation coefficients of −0.09 to −0.31 ($p < 0.01$).

Table 5. Performance values (%)[a] for the biking schedules generated from each set of trips.

Parameter[b]	E-bike trips	Matched on A-G[c]	Matched on A-G-P	Matched on A-G-T	Matched on A-G-P-T	Unmatched conventional bicycle trips
ATS	5.98	5.23	5.46	2.93	1.22	1.54
AMS	5.81	5.41	5.43	3.55	1.02	1.65
PTI	7.55	4.29	0.83	18.59	6.21	5.35
PTC	0.02	2.09	2.41	0.35	3.41	0.73
AAA	0.17	7.61	5.17	0.10	0.74	2.09
PTA	1.33	0.07	0.20	2.65	2.12	2.93
PTD	0.67	0.11	1.10	1.64	1.28	3.61
APW	0.76	1.07	5.27	3.31	0.75	1.08
AAG	3.21	0.86	0.07	2.46	0.60	0.55
PTPG	0.37	0.53	0.73	0.22	0.77	0.15
PTNG	0.73	0.50	0.92	0.34	3.93	0.36
SAGPD	0.10	0.09	0.09	0.09	0.08	0.09
Overall PV	1.78	1.80	1.78	2.34	1.51	1.30

[a]Performance value calculation is described in Section 2.2.
[b]Parameter definitions, including units, are in Table 1.
[c]A: Age, G: Gender, P: Trip purpose, T: Terrain.

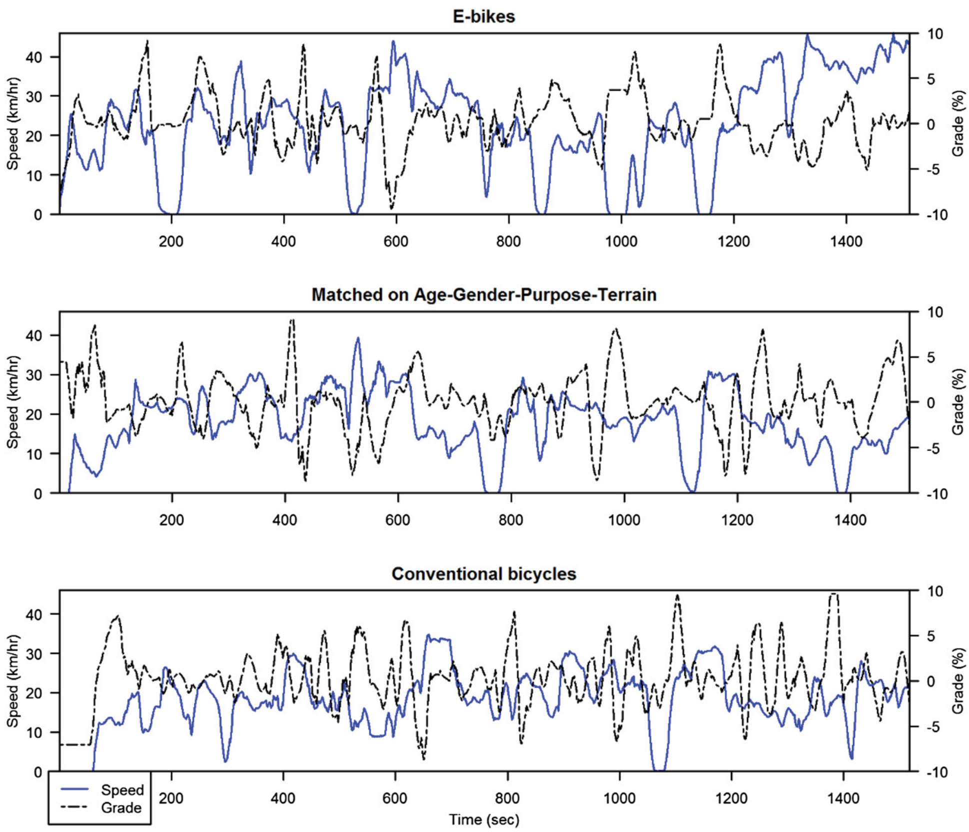

Figure 3. Biking schedules representing e-bike, matched, and unmatched conventional bicycle trips.

Figure 4 shows the cumulative moved distance and motive energy over the six biking schedules. The average total distance over 25 min for the 5 conventional bicycle schedules is 7.2 km and for the e-bike schedule is 9.7 km, reflecting the higher average speed of e-bikes. The motive energy required to produce the observed travel dynamics of e-bike trips is substantially higher than that of conventional

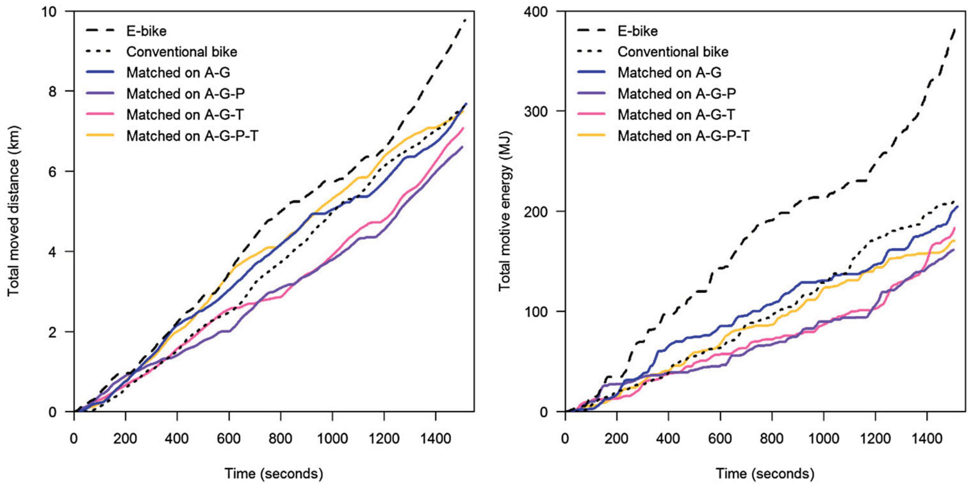

Figure 4. Cumulative distance (left) and motive energy (right) over each biking schedule.

bicycle trips. The average motive power of the e-bike schedule (256 W) is twice as large as that of the conventional bicycle schedules (107 W to 140 W, highest for the full/non-matched sample).

As an illustration to parse the effects of speed dynamics from average speed and resistance factors, the average power of the e-bike and four-way matched sample schedules was 256 W and 113 W, respectively (127% higher for e-bikes). Removing dynamic effects by calculating the power for steady-state riding at the average moving speed and average absolute grade of each sample (from Table 4) yields power estimates 88% higher for e-bikes. Further removing the effects of different physical resistance by applying the conventional bicycle weight and resistance parameters to both power calculations yields steady-state power estimates 57% higher for e-bikes. Thus, of the 127% power difference, roughly half can be attributed to average speed and grade differences, a quarter to resistance differences, and a quarter to differences in speed and grade dynamics.

4. Discussion

The sample is considered generally representative of the regional cycling population in terms of socio-demographics, with some exceptions. Children (under age 14) are excluded from the sample, which is not a major issue for this study because they are not legally allowed to ride e-bikes in the province. Still, the dynamics of conventional bicycle trips reported here only apply to adult cyclists. The sample skews older (see Figure 2), likely because of the targeted recruitment of e-bike riders, who tend to be older. Finally, the sample could be unique in other ways besides socio-demographics. In particular, cyclists willing to participate in a moderately burdensome study such as this could be more avid or keen about cycling than others.

The trips by e-bike in this sample were made by older riders than the conventional bicycle trips, consistent with past research (Fishman and Cherry 2016). The e-bike trips were also used more frequently for commuting purposes, consistent with a recent study in the United States (Ling et al. 2017). Significant differences between the matched and full conventional bicycle samples support the importance of comparing similar trips when assessing the unique attributes of travel by e-bike. A general comparison of (unmatched) trips on the two types of bicycles underestimates the differences of e-bike travel characteristics. For example, e-bikes tend to be used by older riders; matching on age leads to lower speeds for the matched conventional bicycle trips (Table 3), and thus greater differences from e-bike trips. On the other hand, e-bikes tend to also be used more for work trips, which can have the opposite effect.

The average speeds (ATS, AMS) for e-bike trips were 6 km/h faster than the matched conventional bicycle samples (22 versus 17 km/h). Average e-bike speeds around 30% faster than conventional bicycles is toward the upper end of the range reported in previous studies (Baptista et al. 2015; Flügel et al. 2017; Langford, Chen, and Cherry 2015; Schleinitz et al. 2017). Percent time idling (PTI) was not significantly different, implying similar effects of traffic control devices on stopped time. But e-bikes spent less time cruising and more time accelerating and decelerating than conventional bicycles. E-bikes also had significantly greater absolute acceleration, which supports the hypothesis that e-bike speeds are more dynamic. Greater speed dynamics for e-bikes is potentially reflective of lower acceleration costs perceived by riders, which may lead to cyclists riding less strategically to avoid accelerations. In past surveys, assistance in acceleration was cited as a key benefit for e-bike users (MacArthur, Dill, and Person 2014; Rose 2012).

The terrain characteristics were similar between e-bike and conventional bicycle trips, although e-bikes spent a slightly smaller percentage of time on positive grades. Less time on positive grades but similar time on negative grades could reflect similar terrain but grade-dependent speed differences (i.e. less time ascending similar hills). A larger difference between electric and conventional bicycle speeds on positive versus negative grades was reported in a recent observational study in Norway (Flügel et al. 2017). In a previous online survey, 35% of e-bike riders stated they avoid hills less on e-bikes than conventional bicycles (MacArthur, Dill, and Person 2014), but no such systematic terrain difference was observed in this study.

The speed and grade dynamics of the samples of electric and conventional bicycle trips in this study were successfully represented in 25-minute biking schedules, evidenced by good performance values under 3% for all six generated schedules. The schedules represent not just the speed dynamics but the interacting speed-grade dynamics of the observed trips, which are important because the effects of motor assistance on riding behaviour are expected to be grade-dependent (Bigazzi and Lindsey 2019; Flügel et al. 2017). Higher average speeds are reflected in 2.5 km (35%) longer riding distance in the e-bike than conventional bicycle schedules. The e-bike schedule also requires twice the motive energy of the conventional bicycle schedules. All of the matched sample schedules require less motive energy than the pooled conventional bicycle schedule, magnifying the higher energy demand of e-bike travel when comparing trips with similar rider demographics and trip purposes. The motive energy differences are larger than the distance/speed differences because they include the impacts of greater speed dynamics (Table 4) as well as greater weight and resistance parameters (Tengattini and Bigazzi 2018).

5. Conclusions

This paper goes beyond average speed differences to quantify and compare the speed and grade dynamics of urban trips on electric and conventional bicycles. Archetypal cycling dynamics are presented in the form of biking schedule data for each type of bicycle. The results show that cyclists change their microscopic travel behaviour in several ways in response to electric motor assistance, as suggested in a recently-developed behavioural speed choice model (Bigazzi and Lindsey 2019). Although human energy expenditure may be reduced when riding e-bikes (Langford et al. 2017), cyclists also increase both their average speed and their speed dynamics to utilize the additional available motive power. Greater speed dynamics combined with higher average speed and greater resistance factors substantially increases the total motive power and energy required for typical operation of these bicycles. The differences in speed dynamics and motive power are important for understanding and modelling microscopic travel behaviour of cyclists, with applications including vehicle design, facility and signal design, and safety and health evaluation.

A key application of this research is design and testing of electric bicycles, including development of realistic range estimates for real-world usage. The electric biking schedule can be used to simulate or lab-test battery state-of-charge over typical riding conditions. It could also be used in the design of motor controllers and other vehicle components such as regenerative brakes. Another application is investigation of human energy expenditure and breathing rates on different types of bicycles through physiology testing and modelling, such as in a recent effort to design e-bike systems that can reduce inhalation of traffic-related air pollution (Sweeney et al. 2018). The joint speed-grade dynamics are particularly important for these applications because of the grade and history dependence of energy requirements to cycle at a given speed (Bigazzi and Figliozzi 2015).

Further work could be done to enhance the biking schedule generation method. This is still a relatively new method, derived from motor vehicle studies, and future research should examine other methods of determining the optimal number of clusters, additional assessment parameters, and alternative weighting in the PV calculation. Another limitation in the analysis is the reliance on GPS data for speeds and DEM data for road grades. Both data sources have errors, and more research is needed to determine the best GPS data processing and road grade extraction techniques for cycling trips. The potential data errors introduce uncertainty into the analysis, but are not expected to substantially affect the findings because they would likely be similar for electric and conventional bicycle trips.

The scope of study is another limitation, particularly with regard to terrain. The survey was conducted in a single, moderately-hilly region. While the survey sample is believed to be generally representative of regional cycling, the speed dynamics of these same riders would likely be different in another city. Within this part of the North American continent, for example, Vancouver is more hilly than Portland, Oregon but less hilly than Seattle, Washington. In addition, although a specific effort was made to recruit e-bike riders, with uptake in North America still low, the sample size was not large. Future research could combine e-bike data from multiple cities to develop biking schedules representing e-bike travel characteristics in a broader range of contexts. With additional data, e-bike schedules could be parsed by terrain, e-bike style (pedal-assist, throttle-assist, cargo, speed-pedelec, etc.), and other factors (demographic, climate, road facility, trip purpose). With sufficient monitoring data, bikeway volumes could also be included to account for traffic impedance (Bernardi, Krizek, and Rupi 2015; Jin et al. 2015; Xu et al. 2016). Regulatory e-bike schedules could then be developed to provide consumers with standardized range estimates, similar to the driving schedules used for fuel economy labelling of motor vehicles.

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