Analyzing the Usage Patterns of Electric Bicycles

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ABSTRACT

We analyze over 100 Gb of electric bicycle (e-bike) usage data collected through the University of Waterloo WeBike field trial. The WeBike fleet consists of 31 instrumented e-bikes used by University of Waterloo faculty, staff and students. We break down usage and battery charging habits by gender and by occupation, and we compare participants' initial estimates of how much they thought they would ride their e-bike with their actual riding histories. We also discuss data pre-processing challenges such as identifying trip start and end times from noisy and incomplete sensing data.

1. INTRODUCTION

Electric bicycles (e-bikes), equipped with a battery and a motor that provides assistance to the rider, are an emerging mode of transportation that is clean, inexpensive and healthy. They are no longer a niche technology: there are more than 200 million e-bikes in use in China alone [13], with rapidly dropping prices and increasing quality. Thus, it is important and timely to study e-bikes and their impact on travel behaviour, the electricity grid and public health.

To do so, we are conducting a three-year field trial at the University of Waterloo, called WeBike [14], with 31 e-bikes given to selected professors, staff members and students. Each bike is equipped with a sensor kit that captures GPS coordinates, movement and battery charging current every minute (details in Section 3). Additionally, before the field trial began, each participant was asked to estimate how much he or she would ride their e-bike.

In this paper, we analyze over 100 Gigabytes of WeBike usage data collected since the beginning of the project in Summer 2014 till the end of the 2015 cycling season (October). We make the following contributions:

1. We show how to identify trips from the per-minute data feeds generated by the e-bikes; while this may seem simple, challenges arise due to noisy and incomplete sensing data.

2. We present a break-down of trip statistics and battery charging habits for male vs. female participants and for faculty/staff members vs. students.

3. We compare participants' initial estimates of how much they would ride their bikes with actual riding histories.

EV-Sys, June 21-24, 2016, Waterloo, ON, Canada
 ISBN 978-1-4503-4420-3/16/06. . . $15.00
DOI: http://dx.doi.org/10.1145/2939953.2939955

2. RELATED WORK

In our literature review, we identified five recent e-bike field studies, summarized in Table 1. The two closest to ours are Fyhri & Fearnley [6] and Paefgen & Michahelles [10], which also focus on usage patterns. The former collected odometer data and reported a statistically significant increase in trip frequency and distance for participants who were given e-bikes versus those in a control group who used regular bicycles. The increase was greater for female participants. The latter involved 17 e-bikes with GPS loggers available for loan to employees of an insurance company. However, only preliminary results from two e-bikes were presented, suggesting that the bikes were used mainly for commuting, with many trips taking place during morning and afternoon rush hours.

Two studies focused on safety. Dozza et al. [5] used extensively instrumented e-bikes, with cameras and braking pressure sensors, to analyze near-collisions and other safety-critical events. They found that the higher speed of e-bikes may lead to more hazardous interactions with motorized vehicles. They also reported an average trip duration of 14 minutes and average speed of 17 km/h. Langford et al. [9] analyzed GPS data from a bike-sharing fleet at the University of Tennessee, Knoxville, and discovered that e-bike and regular bike users (mostly male students) engaged is similar types of unsafe behaviour, including not coming to a full stop at red lights and stop signs and going the wrong way on one-way streets. They also found that e-bikes were ridden faster than regular bikes on streets (13.3 km/h vs. 10.5 km/h on average), but not on shared-use paths.

One study, Schleinitz et al. [12], concentrated on speed and found a statistically significant increase in the speed of e-bikes compared to regular bikes. Furthermore, riders 40 years old or younger were faster than riders over 65 years old.

Finally, several surveys of e-bike owners in China (see, e.g., [1, 3]), Europe (see, e.g., [8]) and the United States (see, e.g., [4, 11]) have been reported. Their findings align with those of the field trials, e.g., that e-bikes are ridden faster and for longer distances, and are often used for commuting.

The WeBike field trial is novel in several ways. For one, it is significantly longer than most of the previous studies: it will run for three years till 2017. For another, we are collecting battery-related data in addition to GPS data to analyze charging patterns (and have already used battery discharge data to develop a range prediction model for e-bikes [7]). However, to keep costs and complexity low so that the e-bikes can be used for several years without constant maintenance, we have not installed cameras or any other specialized sensing equipment.

Table 1: Summary of previous e-bike field studies

Reference	Purpose	Location	Participants	Duration	Data Collected
Fyhri & Fearnley [6]	Usage	Norway	66	2-4 weeks	Odometer
Paefgen & Michahelles [10]	Usage	Switzerland	17	4 months	GPS
Dozza et al. [5]	Safety	Gothenburg, SE	12	2 weeks	Video, GPS, braking force, lateral movement
Langford et al. [9]	Safety	Knoxville, TN, USA	12 bikes	2 years	GPS
Schleinitz et al. [12]	Speed	Germany	85	4 weeks	Video, Speedometer

Figure 1: An eProdigy Whistler used in the WeBike field trial

Figure 2: Sensor kit for the WeBike project

3. THE WEBIKE PROJECT

The WeBike field trials involves 31 participants, selected based on their answers to survey questions about their opinions on various modes of transportation and how much they would ride their e-bike. 18 participants are male and 13 female; 16 are professors or staff members at the University of Waterloo and 15 are students. Each participant was given an e-bike and will be able to keep it at the end of the project.

Figure 1 illustrates the eProdigy Whistler mountain bike selected for the project. The electric motor is mounted at the bottom bracket and the battery is located on the down-tube. The bike weights 21kg, including the 2.5kg battery. The motor provides assistance up to a maximum speed of 32 km/h; it spins whenever the rider is pedalling, or the bike may be used in electric-only mode without pedalling. The battery is detachable for recharging, which takes about 4-5 hours from empty, and can be plugged in to a regular wall outlet. The manufacturer-reported maximum range is 45 km.

Each bike is equipped with a digital display that shows battery voltage, speed and mileage. Since voltage is a rough approximation of battery state-of-charge, participants are aware of the (approximate) battery level at all times.

The digital display does not store or transmit any data. For data collection, we use custom-designed sensing hardware located in the box on top of the battery. Figure 2 shows the components when removed from the box; see [14] for an assembly guide. A Samsung Galaxy III smart phone is powered by the bike's battery and provides GPS coordinates, angular speed (in all 3 axes; via the gyroscope) and acceleration (in all 3 axes) through the standard Android API. Additionally, a Phidget voltage sensor measures the battery voltage, a Phidget current transducer measures the battery charging current, a Digikey current transducer measures the battery discharge current, and a Digikey sensor measures the temperature of the battery.

Since the WeBike field trial is long-running and our participants are not dedicated volunteers, we aimed to make the data collection as simple and non-intrusive as possible. We made travel logs optional and do not require the participants to press a button to start recording data before they start riding. Instead, we configured the smart phones to wake up for 4 seconds every minute and collect four data samples, one per second, from all the sensors. We chose not to collect data more frequently to avoid draining the bike's battery and therefore reducing its range (even at the current sensing frequency, the phone alone would drain the battery in less than a week). We chose a wake-up window of 4 seconds because we found that it takes at least 2 seconds to obtain a GPS fix after the phone wakes up. Data are buffered on the phone and uploaded to a MySQL database server via wi-fi whenever available. Each participant also has access to their data via a Web interface. As of October 2015, we have collected over 100 GB of data.

4. TRIP IDENTIFICATION

Since data are collected every minute, even when a bike is not in use, we need to identify trip start and end times. Our initial attempt using GPS data was unsuccessful for two reasons. First, since most of the participants stored their bikes indoors, it takes 1-2 minutes at the beginning of the trip to obtain the first GPS fix. Second, GPS fixes coming from a parked bike were often several hundred meters apart, falsely implying movement.

Instead, we use the phone's gyroscope and linear acceleration sensor. A potential trip starts when either one of these sensors detects movement and ends if there has been no movement for 5 minutes. Consecutive potential trips with a gap of less than 5 minutes between them are merged to account for traffic lights. Finally, we discard trips shorter than 5 minutes (e.g., short test-rides or sensor noise) and those with an average speed of over 25 km/h (most likely corresponding to an e-bike being taken on a bus).

To validate our method, we obtained the true start and end times of 225 trips, made in April and May 2015, from participants who had maintained detailed travel logs. We missed five of these trips because they were just under 5 minutes long (false negatives) and identified two short spurious trips (false positives) likely due to noise in the measurements. Reducing the minimum trip duration eliminated the false negatives but added more false positives. Furthermore, we found that, on average, the trip durations computed by our method were within 5 percent of the actual durations.

5. DATA ANALYSIS

This section presents our analysis of trips, battery charging patterns and differences between anticipated and actual riding. We use the t-test at 95% confidence level when reporting differences between mean trip durations or speeds across sub-populations such as male vs. female participants. The bar charts in this section are histograms, with probability-normalized frequency on the y-axes. Table 2 summarizes the 4668 detected trips by gender and occupation; trip durations are measured in minutes.

Note: Recall from Section 4 that every trip is missing GPS data for the first 1-2 minutes; furthermore, we found that most e-bikes had missing GPS data during trips. This prevented us from reconstructing trip trajectories and analyzing trip distances and average speed. Instead, the trip statistics reported in this section are based on trip durations.

Table 2: WeBike trip statistics

	Total	Female	Male	Student	Staff/ Faculty
Number of trips	4668	2124	2544	2470	2124
Avg. num. of trips per participant	156	163	141	164	137
Avg. trip duration per participant	16.8	15.8	17.6	16.5	17.7

5.1 Trip Statistics

Start times. Figure 3 plots the trip start times with hour-of-day on the x-axis. The two peaks occur during morning and afternoon rush hours, suggesting that participants use their e-bikes mainly for commuting. There are virtually no trips between 10pm and 5am. Figure 4 shows the distributions of trip start times for men and women separately; there are no obvious differences. On the other hand, Figure 5 suggests that students ride less than staff and faculty in the morning (7-10am) but more in the evening (after 6pm).

Trip duration. Figure 6 shows the distribution of trip durations (in minutes) in black, and the cumulative distribution in grey. Over 70 percent of all trips are under 20 minutes long. Figure 7 breaks down the durations by gender and Figure 8 by occupation. Male participants and faculty/staff appear to make longer trips (significant with a p-value of 0.0001; also evident in Table 2).

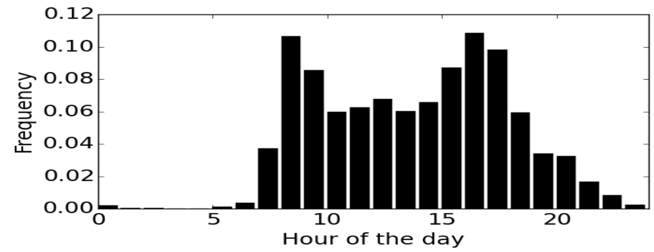

Figure 3: Distribution of hour of the day when trips started

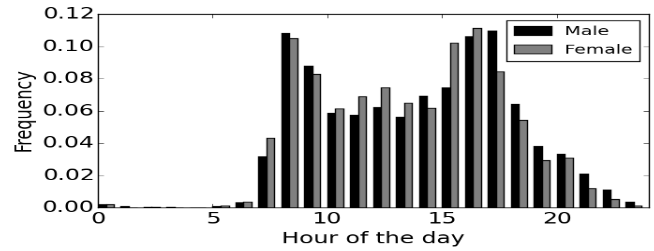

Figure 4: Distribution of hour of the day when trips started divided by gender

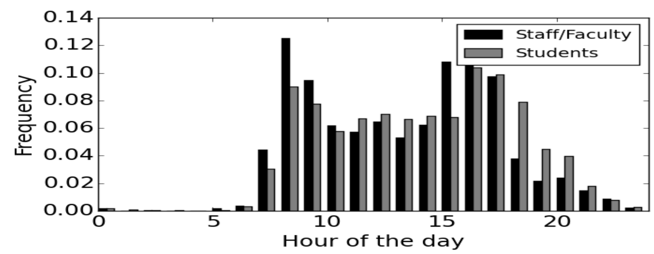

Figure 5: Distribution of hour of the day when trips started divided by occupation

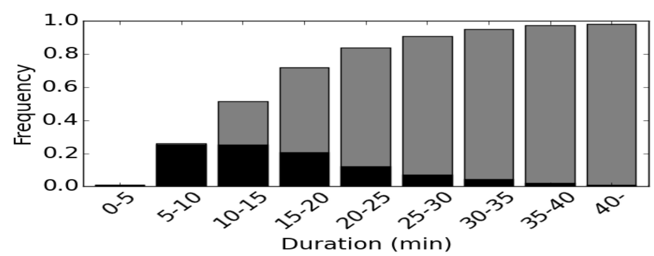

Figure 6: Distribution of trip duration

Trips per month. Figure 9 shows the frequency of trips with month of the year on the x-axis. Most trips happened between May and October, with a dip in August due to vacations. However, despite the cold winters in Waterloo, some participants did ride their e-bikes all year. Breakdowns by gender and occupation did not provide additional insight and are omitted for brevity.

5.2 Battery Charging Statistics

Next, we analyze over 2000 battery charging events recorded in our dataset, identified as periods of time with non-zero charg-

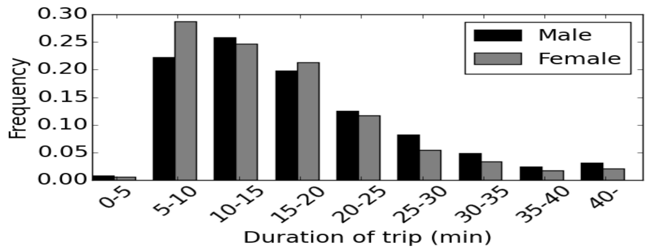

Figure 7: Distribution of trip duration divided by gender

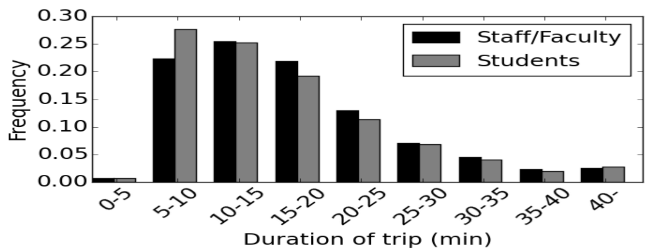

Figure 8: Distribution of trip duration divided by occupation

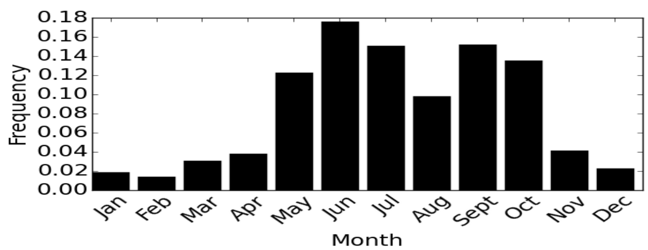

Figure 9: Distribution of trips per month

ing current. Table 3 provides an overview of the average number of charging events per participant and the average number of trips made between charges. Since males and staff/faculty have longer trips (recall Table 2), they have fewer trips per charge.

Table 3: Battery charging statistics

	Total	Female	Male	Student	Staff/ Faculty
Charging events	2007	791	1216	927	1080
Average per participant	67	61	68	62	68
Average trips per charge	2.3	2.7	2.1	2.7	2.0

Charging start times. Figure 10 plots the distribution of charging events by the hour of the day they started at. Comparing to Figure 3, participants tend to charge batteries right after they come to work in the morning and right after they arrive home in the afternoon and evening. Figure 11 separately shows the distribution of charging start times for male and female participants. Interestingly, it appears that more men charge their batteries after 7pm. Finally, Figure 12 shows that students have more charging events after 6pm than faculty/staff, which is consistent with Figure 5 (students make more evening trips).

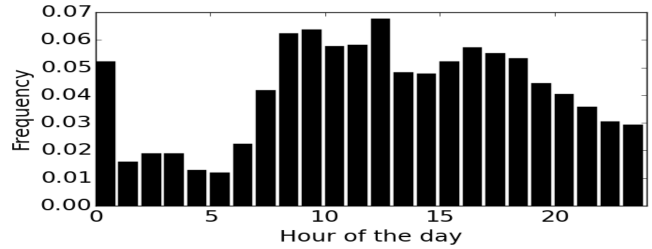

Figure 10: Distribution of hour of the day when charging events started

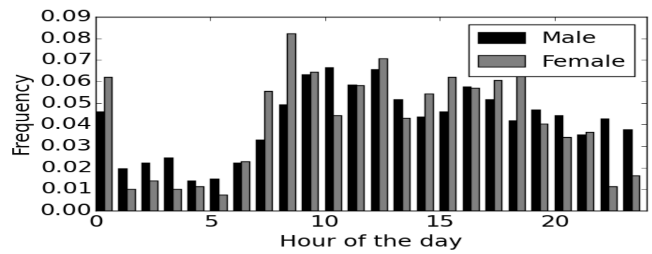

Figure 11: Distribution of hour of the day when charging events started divided by gender

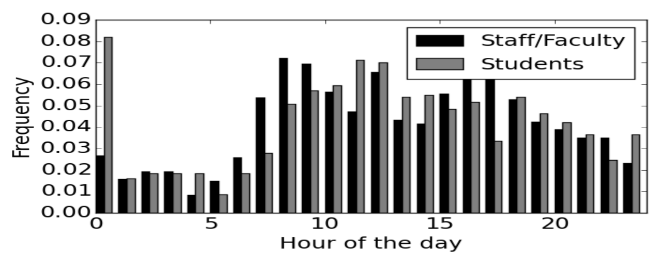

Figure 12: Distribution of hour of the day when charging events started divided by occupation

Battery level at the beginning of charging. Here, we examine how full the battery was (state-of-charge) at the beginning of charging. Figure 13 shows charging events for different levels of state-of-charge (SOC)[1]; note that SOC=0 means that the battery was empty. The frequency distribution is shown in black and the cumulative frequency in grey. Only ten percent of charging events occurred when the battery was less than 10 percent full. Most of the time, batteries were at least 30 percent full when they were plugged in for charging. In fact, over a quarter of all charging events started when the battery was nearly full.

Figure 14 shows a breakdown of SOC at the beginning of charging by gender. It appears that men kept their batteries fully charged, even if nearly full, more often than women. Similarly, Figure 15 suggests that staff and faculty topped up their batteries more often than students.

[1]We calculated SOC at the beginning of charging using battery voltage, as described in Chapter 8 of [2].

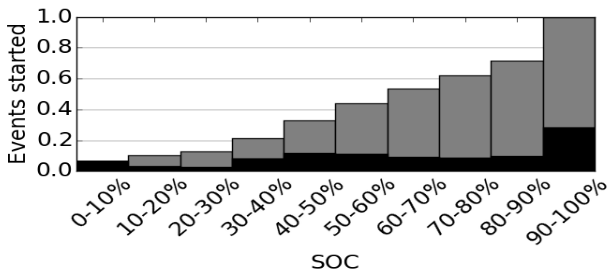

Figure 13: Distribution of state-of-charge at the beginning of charging

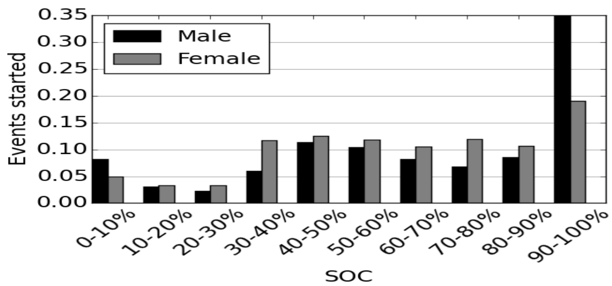

Figure 14: Distribution of state-of-charge at the beginning of charging divided by gender

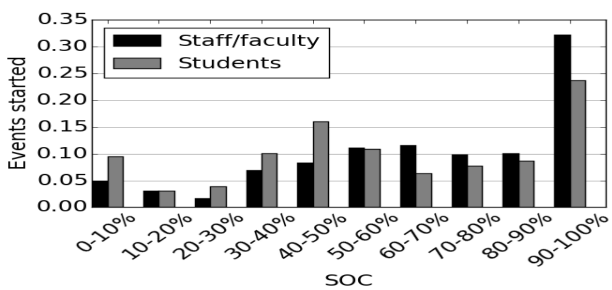

Figure 15: Distribution of state-of-charge at the beginning of charging divided by occupation

5.3 Anticipated vs. Actual Riding

In the pre-trial survey, each participant was asked to estimate the number of kilometres per week that they would ride their e-bike in the summer and how often they would ride in the winter. We now study the correlation of the responses with actual trip data. Since we were unable to reliably compute the total number of kilometres ridden due to spotty GPS data, we use trip duration, in minutes, and the number of trips as indications of actual riding frequency.

Summer riding. Figure 16 shows a scatter plot with the anticipated number of km/week on the x-axis and the average number of minutes ridden per week on the y-axis. Each data point represents one participant. There is no obvious trend and the Pearson correlation coefficient is only 0.18. The only participant who anticipated 30km/week had the most actual minutes ridden (top right corner of the plot). However, the next two participants who estimated 25km/week rode significantly less, in fact less than many participants who estimated they would ride fewer than 25 km/week.

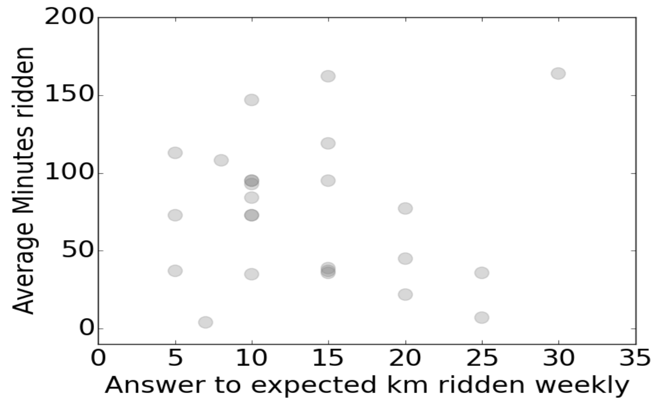

Figure 16: Correlation between expected distance per week (survey) and average summer minutes ridden per week

Similarly, Figure 17 shows a scatter plot with the anticipated number of km/h per week on the x-axis, as before, but with the average *number* of trips per week on the y-axis. Again, there is no obvious correlation and the Pearson coefficient is only -0.03.

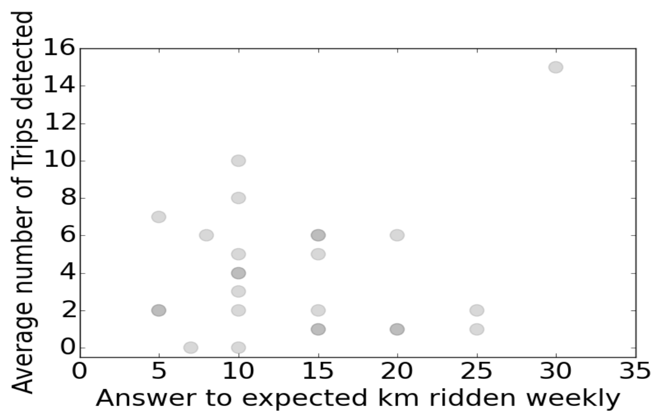

Figure 17: Correlation between expected distance per week (survey) and average number of summer trips per week

Winter riding. We observe a similar lack of correlation for winter riding. Figure 18 and Figure 19 plot the anticipated number of km/week on the x-axes, versus the average minutes ridden per month and number of trips per month, respectively, on the y-axes. However, two of the participants who said they would ride their e-bike frequently in the winter (1-3 times per week) do have the most trips and minutes ridden.

6. DISCUSSION AND CONCLUSIONS

The main findings from the WeBike data so far are as follows.

- E-bikes are mainly used for commuting during the cycling season, and for trips under 20 minutes long, though at least three participants continue to ride regularly in winter.
- On average, men's trips tend to be slightly longer than women's.

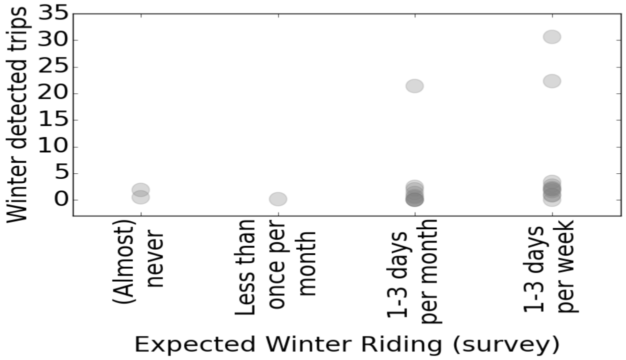

Figure 18: Correlation between usage (survey) and average minutes ridden per month

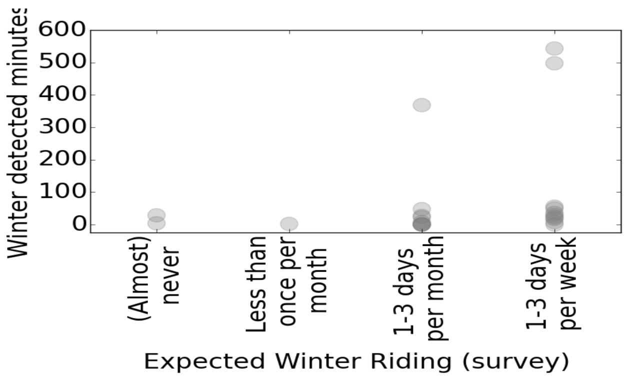

Figure 19: Correlation between usage (survey) and average trips ridden per month

- E-bikes are rarely used at night, but students are more likely to ride in the evening than faculty and staff.
- There is little correlation between the anticipated usage frequency before the field trial began and actual usage.
- E-bikes tend to be charged right after trips. When charging begins, the battery usually still has at least 30 percent of charge remaining.

Some of our results are similar to those in previous field trials and owner surveys, namely that e-bikes are often used for commuting and that men tend to ride more than women. Our average trip durations are similar to those reported in European and American e-bike field trials, but the trip durations reported by riders in Shangai and Kumming, China, were significantly longer, at 20-25 minutes [3].

Additionally, we have obtained new insight into the usage patterns of e-bikes. For example, the lack of correlation between anticipated and actual usage suggests that potential buyers may be unfamiliar with e-bikes and their capabilities. Furthermore, e-bike manufacturers may consider built-in fenders and lights for winter and evening riding.

As for our charging analysis, one may argue that charging the battery when it is not close to being empty indicates range anxiety: the fear of running out of power before reaching the destination. However, WeBike participants were instructed to keep their batteries fully charged to extend battery life. The charging events when the battery was nearly full likely happened when the bike was not in use and only the smart phone was consuming the bike's battery.

The WeBike field trail will continue till 2017. As we collect more data, we have the following directions in mind for future work:

- Reconstructing trip routes and speeds from sparse GPS data.
- Investigating factors affecting battery degradation. Does winter cycling prematurely wear out the battery?
- Classifying riders into categories based on trip lengths/durations, average speed and battery consumption.
- Have usage habits changed over the course of the WeBike field trial? Which participants are riding more/less?

7. ACKNOWLEDGEMENTS

Funding for this research was provided by Cisco Systems and the Natural Science and Engineering Research Council of Canada (NSERC).

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