How Similar is the Usage of Electric Cars and Electric Bicycles?

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ABSTRACT

Electric vehicles (EVs) are expensive. An intriguing idea that was recently proposed is to use a fleet of electrically-assisted bicycles (eBikes) to model the usage and charging patterns of a fleet of EVs at a much lower pricepoint. In this paper, we make a first attempt to explore this idea using usage data from an EV field trial and an eBike field trial taking place in the same city. Unfortunately, we find that for most features of interest, our eBike and EV datasets are statistically different. However, since both datasets were based on only 10-30 participants, further research into this question is required as more data become available.

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1 INTRODUCTION

The transportation sector is the world's largest consumer of oil and a rapidly-growing source of greenhouse gases. As electricity grids transition to renewable energy sources, EVs have the potential to create a carbon-free and sustainable transportation network. Thus, countries around the world have put strong policies into place to encourage EV adoption. This has made the topic of EV integration into the electrical grid and into the transportation infrastructure a topic of considerable research interest [1, 13].

A significant problem in doing data-driven research in the area of EV integration is that EV fleets are very expensive and therefore out of reach of most researchers. EV manufacturers such as Tesla do collect large amounts of data, but these data are not publicly available. Consequently, researchers are forced to make assumptions about critical parameters such as times when EVs are charged, their state of charge when charging begins, and the duration of charging. However, little is known about whether these assumptions (such as the assumption of Poisson distributed arrival of EVs at charging stations) hold in real life, bringing into question the validity of papers based on these assumptions.

An intriguing idea that has been recently proposed to overcome this problem is to use charging and usage data collected from a fleet of eBikes to model a fleet of EVs [2]. Although this is an interesting proposal, to our knowledge, it has not been scientifically validated. This paper attempts to fill this gap.

We analyze over 70 Gb of data from sensor-equipped eBikes and EVs driven in Waterloo, Ontario, a mid-size metropolitan area in North America. We analyze data from pure electric EVs (e.g., Nissan Leaf) as well as electric-gasoline hybrids (e.g., Chevrolet Volt, Toyota Prius) obtained from a data logger connected to the on-board diagnostics port. We also obtained eBike charging and usage data from the Waterloo WeBike field trial [15]. For both datasets, we compare trip statistics such as start times, end times, destinations, lengths and durations, as well as battery statistics such as charging start times and end times, and state of charge (SoC) at the beginning and end of trips and charging sessions.

Our analysis indicates that for most features of interest, our eBike and EV datasets are statistically different. To the extent that our datasets can be considered to be representative, this

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suggests that eBikes *cannot* be used to model EVs. We caution that our datasets involve only 10-30 participants; larger datasets may lead to less negative conclusions (though we identify several intrinsic differences between these transportation modes that lead us to expect our overall conclusion to hold even with more participants).

2 RELATED WORK

To the best of our knowledge, there is no prior work on comparing the usage and charging patterns of eBikes and pure/hybrid EVs. There is, however, prior work on independently analyzing particular types of electric vehicles, as summarized below.

For eBikes, there are at least six recent field studies. One of these is the WeBike project where we obtained the data for this work [15]. WeBike focuses on eBikes as a new mode of transportation, whereas other studies compare eBikes to regular bicycles [6, 7, 11, 14, 16]. These field studies as well as owner surveys report that eBikes tend to be used more frequently than regular bikes, especially for commuting, and that eBikes tend to be ridden faster and therefore novel safety and policy issues may arise. However, it is not clear from these findings whether eBikes are used similarly to EVs.

For EVs, there have been several field trials, the largest being the UK Ultra Low Carbon Vehicle Programme [9] and the MINI-E trial conducted in Germany and the USA [5]. Additionally, opinions expressed in online EV ownership forums have been analyzed [3]. A main focus of this body of work has been on understanding barriers to the adoption of EVs. Again, it is not obvious from these results regarding EVs only whether eBikes are used or charged in similar fashion.

3 DATA SOURCES AND PREPROCESSING

For EVs, we use data from the Drive4Data project[1], in which 11 owners agreed to have data loggers connected to their cars' on-board diagnostic ports. The loggers collect speed, odometer, GPS, external temperature and battery state of charge (SoC) data. The Drive4Data dataset spans from April 2013 to August 2016, resulting in about 12 GB of raw data and 100 million samples. The car models in the study are shown in Table 1.

For eBikes, we use data collected through the WeBike field trial [15], in which 30 participants were given sensor-equipped eBikes for personal use (mostly for daily commute trips). The sensing kit mounted on each bike includes an Android smartphone, which records acceleration, gyroscope, GPS and temperature data, as well as a battery charge current sensor. Roughly half the riders are male and half are female, and one-third each are students, staff or faculty of the University of Waterloo. Since 2013, about 60 GB of data containing 200 million samples have been collected.

[1]https://wise.uwaterloo.ca/drive4data

Table 1: Cars used in the Drive4Data project

Count	Make	Type
5	Smart Fortwo ED	Pure EV
3	Chevrolet Volt	Hybrid EV
1	Nissan Leaf	Pure EV
1	Ford Focus EV	Pure EV
1	Toyota Prius Plug-in	Hybrid EV

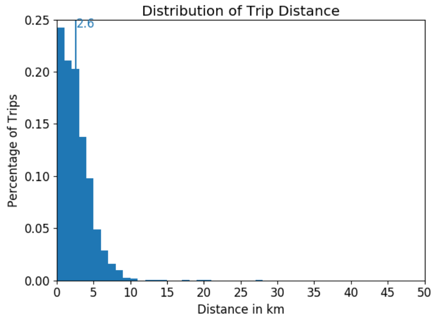
Both data sets were collected in the same general area during roughly the same time span, making them comparable. Additionally, both covered a time span of multiple years and thus were less prone to singularities such as unusual weather in a single season.

To identify trips and battery charging sessions in the WeBike dataset, we used the methodology from [8, 15]. A trip starts if the accelerometer and gyroscope measurements are nonzero for at least a minute and concludes when movement stops. We discarded trips shorter than five minutes, longer than two hours, and those with an average speed above 30 km/h (to filter out trips where the bike is taken on a bus or a train). A charging session starts when the battery charge current sensor starts reporting nonzero values and concludes when the charge current returns to zero.

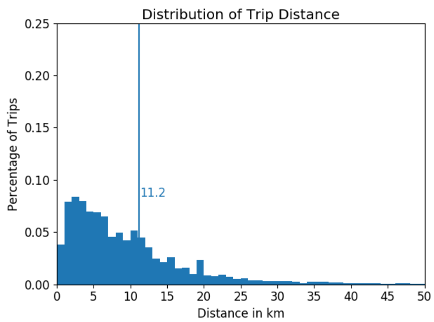
For the Drive4Data dataset, we implemented similar trip and charge detection algorithms. However, instead of acceleration, we used speed to detect trips (speed was measured in this project, unlike with WeBike). Also, instead of the battery charge current, which is not available in Drive4Data, we used SoC data to detect charging sessions. A trip starts when speed becomes nonzero and concludes when the ignition is turned off. We discarded trips shorter than one minute or covering fewer than 100 metres. A charging session starts when SoC increases by at least five percent over one hour (the typical time to charge an EV battery from empty to full is 7-8 hours, or a rate of about 12 percent per hour), and ends when SoC changes by less than five percent per hour.

For some cars, there were very few SoC values below approximately 15% or above 85%. This behavior has also been observed by others [18]. The lack of SoC values outside of this range for some EVs is presumably to prolong the lifetime of the battery as a medium SoC is optimal for Lithium-Ion batteries [10]. Nevertheless, some EVs do report values of up to 100%, which we believe is because they report an SoC value of 100% when the true SoC is actually around 85%. To allow comparisons across EVs, we rescaled the SoC values of each individual car to span the range of 0 to 100 %.

For each trip, we recorded the start and end times, the initial and final battery SoC, the distance travelled (obtained

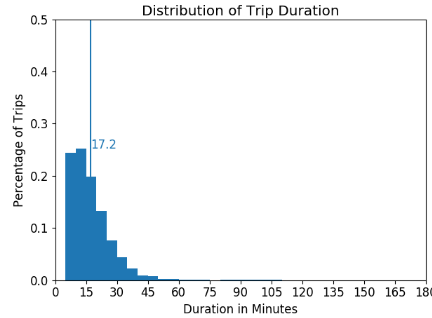


(a) WeBike

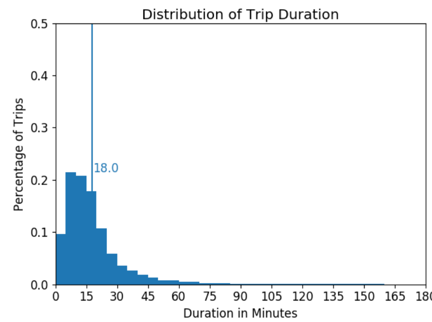


(b) Drive4Data

Figure 1: Trip Lengths



(a) WeBike



(b) Drive4Data

Figure 2: Trip Durations

directly from Drive4Data odometer data or calculated from GPS fixes in WeBike using the algorithm from [8]), and the mean temperature during the trip. We merged consecutive trips if they are less than five minutes apart to account for traffic stops. For each charging event, we recorded the start and end times, and the initial and final SoC.

4 RESULTS

We now compare the distributions of trip and charging attributes in the two datasets. We seek statistically significant similarities or simple transformations that can be used to match distributions, which would allow eBike attributes to model equivalent attributes for EVs. Furthermore, we compare the usage of pure and hybrid EVs versus eBikes.

To begin, we note that, using the Kolmogorov-Smirnov two-sample test [17]–a standard non-parametric test to compare two empirical distributions–with very high confidence, none of the distributions are similar (p-scores less than 10^{-6}). Next, for each attribute, we discuss the reasons why we think this result holds.

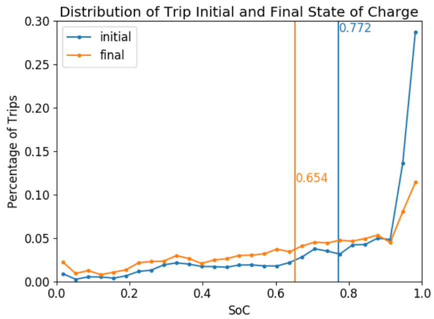
4.1 Trip-related Attributes

4.1.1 Trip Lengths. Figure 1 presents the distribution of trip lengths in both datasets. Vertical lines correspond to the mean values of the given distributions. As expected, cyclists cover shorter distances than EVs, usually below 5 km and rarely above 10km. Long-distance trips (more than 40km) were rare for EVs, possibly due to the limited range of the pure EVs.

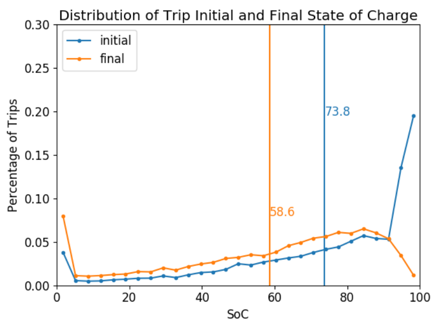
We sought a simple relationship between the distributions which would allow us to emulate EV trips using eBikes. The best transformation we could find by trial and error was $f(x) = 5 * 10^{\frac{x+2}{4}} - 7.5$. While applying this function to the Drive4Data values made them visually similar to WeBike values, the Kolmogorov-Smirnov test [12] resulted in a p-value of only $1.66 * 10^{-7}$, which denotes a very low probability of both samples being drawn from the same distribution.

One of the reasons why we did not find a statistically significant similarity between the distributions is that even though we have a comparatively large data set, it was generated by a relatively small number of participants. Hence, even single participants can potentially have a strong influence on the data distribution. For example, the peak right below 20km in the Drive4Data trip distance distribution is probably the commuting distance of one of the participants.

4.1.2 Trip Durations. Figure 2 presents the distribution of trip durations in both datasets. Unlike trip lengths, trip durations are similar with nearly identical means. This may be due to the fact that, for both types of vehicles, most trips were taken within a mid-sized city. The hard cut-off for WeBike

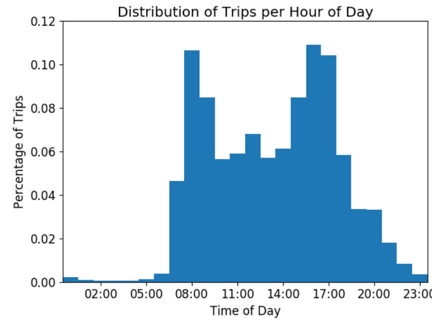


(a) WeBike

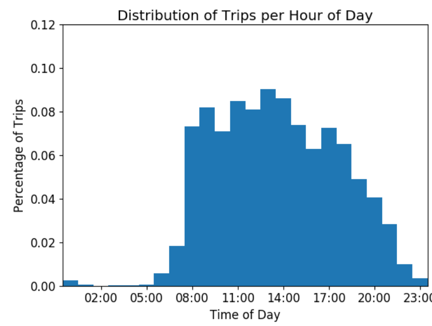


(b) Drive4Data

Figure 3: Initial and Final Trip SoC



(a) WeBike



(b) Drive4Data

Figure 4: Trips for Each Hour of the Day

trips shorter than 5 minutes is due to the minimum trip length our detection algorithm used.

4.1.3 Initial and Final Trip SoC. Figure 3 presents the distribution of initial and final trip SoC in both datasets. Initial SoCs at the start of a trip are quite similar, with most trips starting with a rather high SoC. This is probably due to range anxiety, and an attempt by drivers to reduce the depth of discharge and hence increase the battery lifetime.

The distributions of final SoCs are distinct, with EV final SoCs rarely at 100%, unlike for eBikes. We believe this is due to the many short trips made by eBikes starting with 100% SoC, which minimally deplete the battery, leading to the final SoC also being 100%. In contrast, eBike final SoCs rarely reach 0%, unlike for EVs. This is explained by the presence of hybrid EVs in our dataset, which can continue to drive with an empty battery. We discuss this further when comparing hybrid and pure EVs in section 4.3.

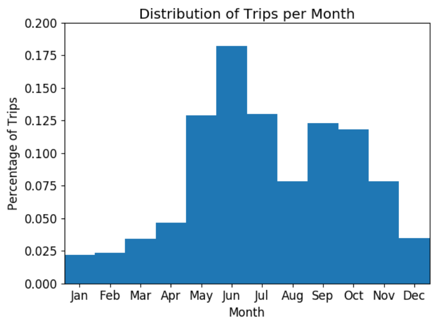
4.1.4 Trips for Each Hour of the Day. Figure 4 presents the distribution of trips for each hour of the day in both datasets. The two distributions are quite different, likely due to how each population used their vehicles. EBikes were mostly used for commuting, leading to distinctive peaks around commute times (8-9am and 5-6pm) with an additional small peak at noon during lunch. Drive4Data usage was more diverse, with a single daily peak.

4.1.5 Trips per Month. Figure 5 presents the distribution of trips per month in both datasets. Car trips are nearly uniformly distributed, with a small dip in February, when winter has the biggest impact on driving conditions. In contrast, bike riding by month is bimodal, with most riding happening in the warmer months, but with a dip during the vacation month of August. Some WeBike riders rode throughout the year, including winter.

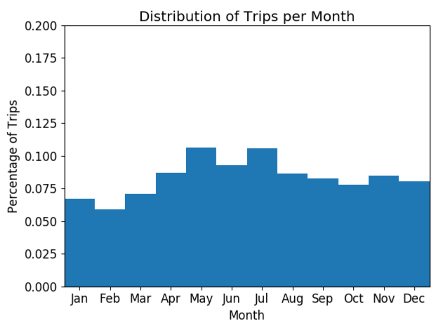
4.2 Charging-related Metrics

4.2.1 Charging Duration. Figure 6 presents the distribution of charging duration in both datasets. Due to the use of similar battery chemistry, we expected charging durations in both datasets to be nearly identical. We found that although charging durations for both vehicles are roughly similar, there are two significant and non-trivial differences.

First, we found few short charge cycles in the EV dataset (i.e., less than 30 minutes), while there were many short charging durations for eBikes. This is likely because the advanced charging system used by an EVdoes not charge the battery if it is already close to being full, because this would have a negative impact on the lifetime of the Lithium-ion battery, while not providing a big benefit to the user. The charging equipment for eBikes, in contrast, does not appear to have such a feature.

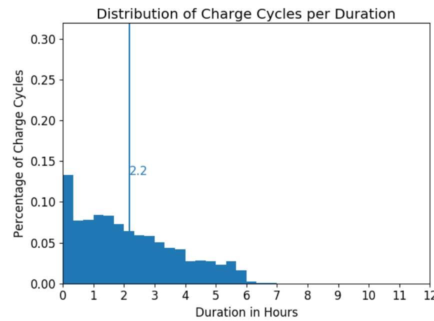


(a) WeBike

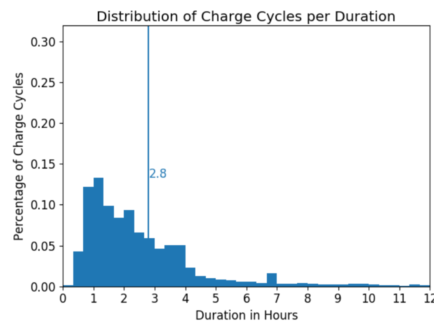


(b) Drive4Data

Figure 5: Trips per Month



(a) WeBike



(b) Drive4Data

Figure 6: Charging Duration

A second difference is that eBike charging rarely exceeds 6 hours, but some EV charging sessions exceed 11 hours. We attribute this to false positives arising from our charge duration estimation algorithm. The SoC can continue to rise after the end of charging due to the 'bounce-back' effect, which leads us to overestimate charging durations for EVs. In any case, there does not appear to be any simple transformation from one distribution to another.

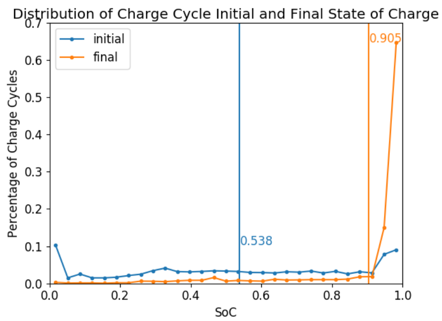
4.2.2 Initial and Final SoC. Figure 7 presents the distribution of initial and final SoC in both datasets. These are quite similar and indicate charging to completion. As discussed in Section 4.2.1, the charging equipment of the bike always charges the battery, even if it is close to being full. In contrast, the EV charger does not charge the battery if it is above about 80% full. We would recommend to to do the same for eBike batteries to prolong their lifetime. See also Figure 10a and Figure 10b for the initial and final SoC during charging for different types of EVs.

4.2.3 Charging Start Times. Figure 8 presents the distribution of charging start times in both datasets. Cars are charged mainly in the afternoon or evening, while bikes are roughly equally charged throughout the day. This may be due to the different participant populations and how the different EVs can be charged. eBike batteries are portable and can be charged from any wall plug using a small power adapter. Many WeBike participants commute to the university and charge their batteries in their office during the workday. In contrast, EV participants are drawn from a different population, and EV batteries can neither be taken out nor charged at any wall outlet. As only a small fraction of employers have parking lots with an EV charging station, charging was probably done mostly at home after work. We hypothesize that with a widespread provision of workplace EV charging, the graphs would be more similar.

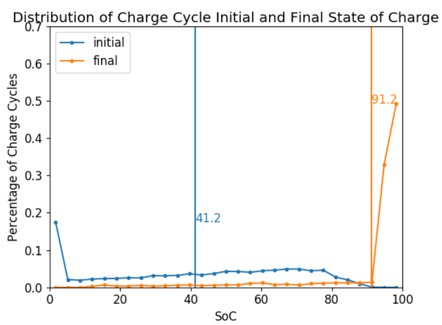
4.2.4 Charging End Times. Figure 9 presents the distribution of charging end times in both datasets. The distributions differ dramatically, again most likely due to the difference in user populations. Comparing Figure 9 with Figure 4, we find that most of the charge cycles (especially for Drive4Data) are completed before midnight, but very few trips start between midnight and 6 am (this was also noted in [19]). Thus, shifting charging times so that charging ends by 6am would not affect comfort while adding flexibility to the charging process. For example, slower charging could improve battery lifetime and could also reduce demand on the power grid [4].

4.3 Hybrid vs. Pure EVs

Since we had data from hybrid and pure EVs in the Drive4Data data set, we compared each of them to eBikes.

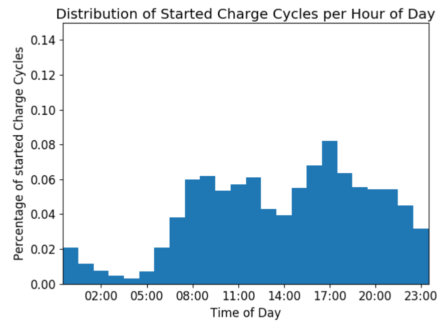


(a) WeBike

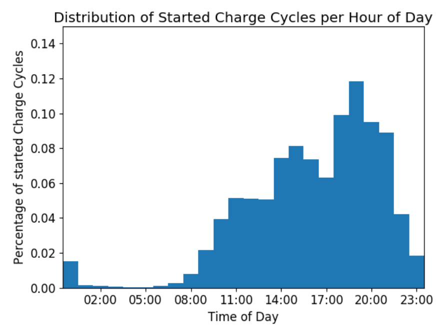


(b) Drive4Data

Figure 7: Initial and Final SoC



(a) WeBike



(b) Drive4Data

Figure 8: Charging Start Times

eBikes are also hybrid vehicles, in that they can be driven by pedaling, so we might expect them to behave more like hybrid EVs than pure EVs.

We found that for the two EV vehicle types, trip durations and distances seem to be quite similar, but the SoC at the beginning and the end of trips (shown in Figure 10) have an interesting characteristic: eBikes seem to lie between pure and hybrid EVs. Specifically, hybrid EVs and eBikes occasionally deplete their batteries to zero, with eBikes somewhere in between pure and hybrid EVs in their behavior. A similar conclusion can be drawn for the distribution of the SoC at the start of trips.

5 CONCLUSIONS

In this paper, we conducted the first study of the similarities and differences in usage and charging patterns of eBikes and EVs. Our study is motivated by a recent idea: to model a fleet of EVs with a much cheaper fleet of eBikes [2]. The analysis was enabled by the availability of real-life eBike and EV usage datasets generated by field trials conducted in the same area.

We found that, in both datasets, trip durations were roughly similar, as were final SoCs. However, we found statistically significant differences arising from three root causes:

- Differences in user populations (commute vs. non-commute); leading to different distributions of times of day when trips start and when charging begins and ends.
- Differences in chargers, due to which EVs not charged when their batteries are nearly full.
- Differences in vehicle types; leading to different distributions of months of operation and trip lengths.

The first issue may not occur in future studies if the the population is more homogeneous, or if the sample size is large enough that a single user would not distort sample statistics. The second issue may disappear if eBikes use a more sophisticated charger, modeled on EV chargers. However, the third issue is fundamental, and is likely to be present in all future eBike and EV data fleets. This leads us to conclude that it is very unlikely that eBikes can be used to uniformly model all aspects of EVs.

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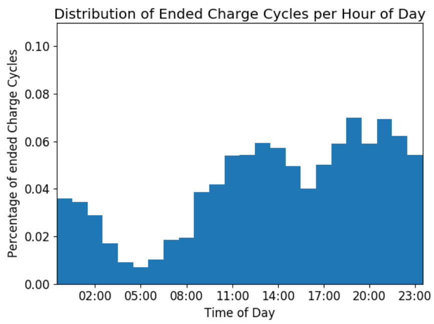
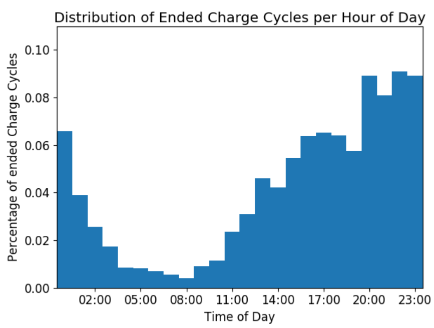
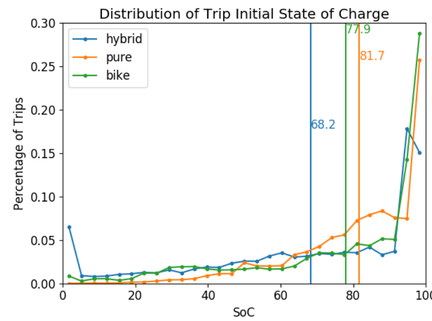


(a) WeBike

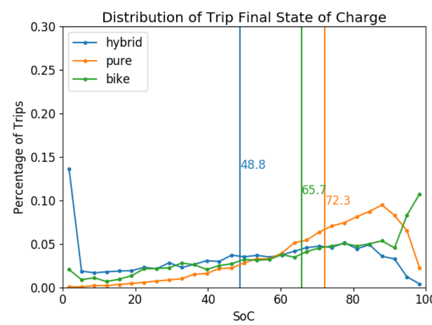


(b) Drive4Data

Figure 9: Charging End Times



(a) Initial SoC



(b) Final SoC

Figure 10: Comparison of Trip SoCs

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