MobiCharger: Optimal Scheduling for Cooperative EV-to-EV Dynamic Wireless Charging

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I. Introduction

With ever increasing concerns on environmental issues caused by gasoline fuel based vehicles, electric vehicles (EVs) have attracted more and more attention from governments, industries, and customers [1]. The recent advancements in EVs have great potential to create a more environmentally friendly smart city. However, due to limited battery capacity, most current mainstream EVs still have quite limited driving range (e.g., 100 miles) [2]. How to ensure the continuous running of EVs on a large-scale road network (e.g., metropolitan city, interstate) becomes a major concern.

To solve the concern, we present *MobiCharger*: a *Mobi*le wireless *Charger* guidance system that determines the number of serving MEDs, and the optimal routes of the MEDs periodically (e.g., every 30 minutes). We studied a metropolitan-scale vehicle mobility dataset, and found: most vehicles have routines, and the temporal change of the number of driving vehicles changes during different time slots, which means the number of MEDs should adaptively change as well. Then, we develop an online method that utilizes Reinforcement Learning to determine the number and the driving route of serving MEDs. Our trace-driven experiments show that compared with previous methods, *MobiCharger* increases the medium State-of-Charge of all EVs by 50% during all time slots, and the number of charges of EVs by almost 100%.

II. Metropolitan-Scale Dataset Measurement

A. Dataset Description and Definitions

In this analysis, we use the data recorded from Jan 1, 2015 to Dec 31, 2015 for measurement, which include:

(1) **Taxicab Dataset.** This dataset records the status (e.g., timestamp, GPS position, velocity, occupancy) of 15,610 taxicabs. 6,510 of them are electric taxicabs.

(2) **Dada Car Dataset.** This dataset is provided by the Dada Car corporation (a customized transit service similar to UberPool), which records the status (e.g., timestamp, position, velocity) of 12,386 electric customized transit service vehicles.

(3) **Charging Station Dataset.** This dataset records the GPS position and number of chargers of 81 existing plug-in charging stations in Shenzhen.

(4) **Road Map.** The road map of Shenzhen is obtained from OpenStreetMap [3]. According to the municipal information of Shenzhen [4], we use a bounding box with coordinate $(lat = 22.4450, lon = 113.7130)$ as the south-west corner, and coordinate $(lat = 22.8844, lon = 114.5270)$ as the north-east corner, which covers an area of around 2,926km^2, to crop the road map data.

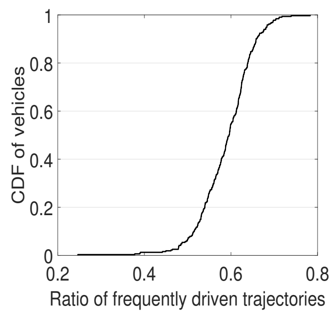

Fig. 1. Distribution of the ratios of frequently driven trajectories.

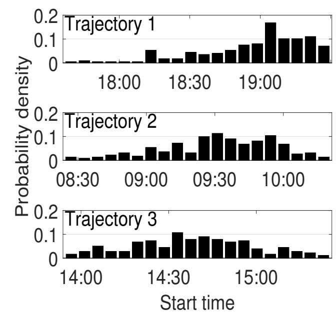

Fig. 2. Distribution of the start times of three vehicle trajectories.

Definition 1: Vehicle Trajectory. A vehicle's trajectory is a sequence of N^e time-ordered landmarks, where each landmark is represented by a latitude and a longitude.

Definition 2: Vehicle Routine. A vehicle's trajectory is a routine if the vehicle's probability of driving the trajectory at around a specific time (the standard deviation of the start times is no higher than the threshold (i.e., 35 minutes in our analysis)) during a time period (i.e., 365 days in our analysis) is higher than a threshold (i.e., 20% in our analysis).

B. Dataset Analysis

1) **Observation 1**: Existence of Vehicle Driving Routines*:* The Cumulative Density Function (CDF) of the calculated ratios of of all the vehicles is illustrated in Figure 1. We can see that for about 80% of the vehicles, more than 55% and maximally about 77% of their trajectories are their frequently driven trajectories. This result implies that most vehicles do frequently drive several similar trajectories in different days. Besides, we are also interested in the start time of the frequently driven trajectories because knowing the trajectories and their start time can exactly tell us where and when the vehicles are likely to appear. Driven by this motivation, we collected the distribution of the start times of each frequently driven trajectory, and randomly selected the results of three trajectories for illustration. Figure 2 shows the histogram of the start times of each selected trajectory. The first trajectory (Trajectory 1) is generally driven at around 19:00 every day, the second trajectory (Trajectory 2) is generally driven at around 09:30 every day, and the third trajectory (Trajectory 3) is generally driven at around 14:30 every day. We can see that

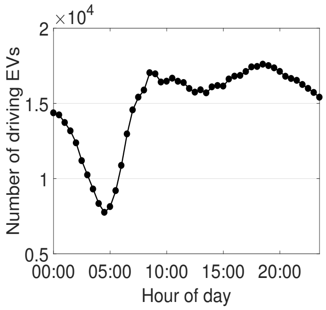

Fig. 3. Number of driving EVs over time.

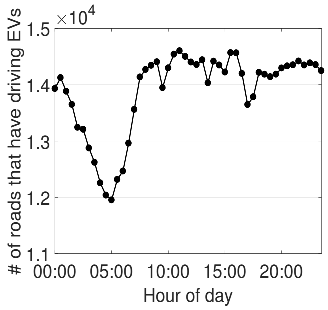

Fig. 4. Number of road segments that have driving EVs over time.

most start times of Trajectory 1 vary within 20 minutes around 19:00 and most start times of Trajectory 3 vary within 30 minutes around 14:30. In contrast, the start times of Trajectory 2 vary over a wider range (as long as 1 hour) around 09:30. This means that the start times of Trajectory 1 and Trajectory 3 vary less than those of Trajectory 2.

2) **Observation 2**: Temporal Change of the Number of Driving EVs*:* Figure 3 shows the calculated average number of driving EVs in each hour of a day. We can see that during the time slots between around 02:00 and 05:00, the number of driving EVs significantly dropped to less than 8,000. This is primarily because that during these time slots, the human transit demand for taxicabs and Dada cars greatly decreased. Some taxicabs and Dada cars chose to stop running during these time slots to save cost. Then the number of driving EVs quickly increased to around 18,000 at around 09:30, which corresponds to the "rush hour" in the morning of a day. At around 12:00, there is a slight drop-down on the number of driving EVs due to reduced human transit demand at noon. Then the number of driving EVs increased to another peak at around 19:30, which corresponds to the "rush hour" in the evening of a day. These results demonstrate that the number of EVs that the MEDs need to support to keep running on the road network varies during different time slots.

We measured the number of road segments that have driving EVs during each time slot in each day throughout the 365 days. Figure 4 shows the average number of road segments versus hour of day. We can see that the change of the number of road segments that have driving EVs is generally similar as the change of the number of driving EVs in Figure 3. However, there are several conspicuous drops of the number of road segments that have driving EVs at around 10:00, 13:00 and 17:00. This may be because that there are not many passengers requesting transit during these time slots, so some taxicabs and Dada cars chose to wait at some places with high likelihood of passenger appearance to save driving cost [1]. From these results, we can conclude that in addition to adjusting the number of the serving MEDs, we should also optimize the driving route of the MEDs.

III. System Design

A. Framework of MobiCharger

1. Vehicle mobility information derivation. First, we apply the *Data Cleaning* (e.g., filtering out positions out of the actual range of Shenzhen, redundant positions). Then, based on the cleaned data, we derive the *Trajectories in Landmarks* of EVs on the *Roadmap with Landmarks and Road Segments* as explained in Section II-A.

2. EV Traffic Density Estimation. Based on the output *Trajectories in Landmarks* from the first stage, we combine the EVs' current trajectories and routines to complete *EV Traffic Density Estimation* for each road segment of the road network.

3. Reinforcement Learning based MED Routing. Based on the real-time status of EVs, we apply the *EV Traffic Density Estimation* to determine the road segments with new changes of EV traffic. Then we train and utilize the *Reinforcement Learning based MED Routing* to decide the place each MED should drive to as a response to the traffic change, and the place can be the originally planned road segment, a new road segment or an MED's nearest parking lot.

IV. Conclusion

Dynamic wireless charging for EVs enables an MED to charge an EV in motion. The deployment of MEDs adaptive to the change of the number of driving EVs is essential for maintaining the SoC of EVs. Our proposed *MobiCharger* is the first to optimize the driving paths of MEDs to minimize the total number of MEDs, maximize the number of encountering EVs of all the MEDs, and meanwhile ensure that each EV has sufficient SoC all the time. Our analytical results on a metropolitan-scale vehicle mobility dataset provide foundation for the design of *MobiCharger*. We utilize the combination of EVs' current trajectories and the EVs' routines to estimate the density of EVs and the cruising graph that the MEDs should cover. Then, we develop an online method that utilizes RL to adjust the driving route of MEDs when the real-time vehicle traffic changes. We conducted trace-driven experiments on SUMO to verify the performance of *MobiCharger*. Compared with previous methods, *MobiCharger* increases the medium State-of-Charge of all EVs by 50% during all time slots, and the number of charges of EVs by almost 100%.

Acknowledgements

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