

CatCharge: Deploying Wireless Charging Lane in Metropolitan Scale through Categorization and Clustering of Vehicle Mobility

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I. INTRODUCTION

The future generation transportation system will be featured by electrified public transportation. To fulfill metropolitan transit demands, electric vehicles (EVs) must be continuously operable without recharging downtime. Wireless Power Transfer (WPT) techniques for in-motion EV charging is a solution [1], [2]. It however brings up a challenge: how to deploy charging lanes in a metropolitan road network to minimize the deployment cost while enabling EVs' continuous operability.

In this paper, we propose *CatCharge*, which is the first work that handles this challenge. From a metropolitan-scale dataset collected from multiple sources of vehicles, we observe the diversity of vehicle passing speed and daily visit frequency (called traffic attributes) at intersections (i.e., landmarks), which are important factors for charging lane deployment. To select landmarks for deployment, we first group landmarks with similar traffic attribute values using the entropy minimization clustering method, and choose better candidate landmarks from each group suitable for deployment. To determine the deployment locations from the candidate landmarks, we infer the expected vehicle residual energy at each landmark using a Kernel Density Estimator fed by the vehicles' mobility, and formulate and solve an optimization problem to minimize the total deployment cost while ensuring a certain level of expected residual energy of EVs at each landmark. Our trace-driven experiments demonstrate the superior performance of *CatCharge* over other methods.

II. METROPOLITAN-SCALE DATASET MEASUREMENT

A. Dataset Description

Our datasets for Shenzhen city record the status (e.g., timestamp, GPS position, speed, occupancy) of vehicles for one month (July 1 – July 31, 2015) and the recording time period is less than 30 seconds. We introduce the datasets below.

- (1) **Taxicab Dataset.** It is collected by the Shenzhen Transport Committee, which records the status (e.g., timestamp, GPS position, speed, occupancy) of 15,610 taxicabs. The daily size of the uploaded data is around 2GB.
- (2) **Bus Dataset.** It is also collected by the Shenzhen Transport Committee, which records the status of 14,262 buses (e.g., timestamp, GPS position).
- (3) **Dada bus Dataset.** It is provided by the Dada Bus corporation (a customized transit service similar to UberPool), which records the status (e.g., timestamp, GPS position, speed) of 12,386 reserved service buses.

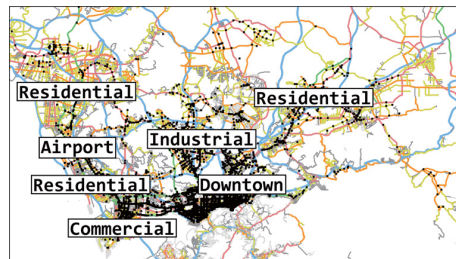


Fig. 1: Distribution of potential positions for placing charging lanes.

- (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 2,926km², to crop the road map data. The retrieved data contains all roads in Shenzhen.

B. Important Issues

There are two main issues that need to be addressed in handling the charging lane deployment challenge:

- (1) **Reducing charging lane length.** The charging lanes need to be as short as possible in order to reduce the deployment cost, while still enabling EVs to be fully charged when they pass a lane. To select locations for charging lane deployment to achieve this objective is non-trivial.
- (2) **Reducing the number of deployed charging lanes.** The problem of determining the locations of the charging lanes on a metropolitan road network to maintain the continuous operability of the EVs on roads, while minimizing the number of deployed charging lanes, is non-trivial.

C. Dataset Analysis

Figure 1 shows the distribution of landmarks (black dots) whose vehicle visit frequency is higher than $10^4/day$, and vehicle passing speed is lower than $60km/h$. The territory of Shenzhen consists of 7 functional regions (e.g., commercial, residential). We can see that each region has several candidate landmarks with both high vehicle visit frequency and slow passing speed.

In Figure 2, we can see the landmarks with both low vehicle passing speed ($60km/h$) and high vehicle visit frequency ($10^4/day$) take up a small portion within the square circle. The above observations motivate us to find an innovative method to properly extract candidate charging lane placement positions considering the diversity in vehicle passing speed and visit frequency, and their distribution in different regions.

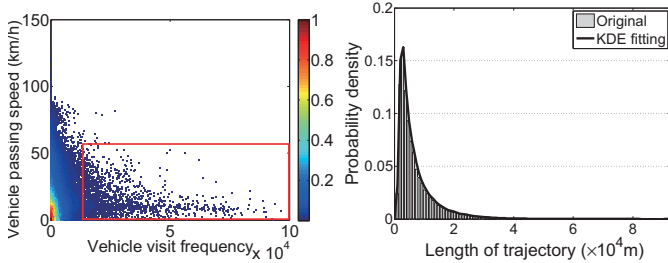


Fig. 2: Density scatter of vehicle passing speed w.r.t. vehicle visit frequency. Fig. 3: Distribution of trajectory lengths & estimation of KDE.

Considering that the vehicles' trajectories reflect their traffic between different locations [5], [6], and the length of a trajectory determines the energy consumption, we calculated the length of the trajectories of each vehicle in one month. The distribution of the collected trajectory lengths is shown in Figure 3. We can see that most of the trajectories are less than 10,000 meters. However, the distribution of the trajectory lengths cannot be simply modeled using a parametric distribution. Since KDE is a non-parametric method to estimate the probability density function of a random variable, we feed the lengths of the trajectories to the KDE model to infer the vehicles' probability of reaching each landmark in the road network. The curve in Figure 3 represents the distribution fitting result from the KDE.

III. SYSTEM DESIGN OF CATCHARGE

As shown in Figure 4, the *CatCharge* consists of following three stages (highlighted as three dashed boxes):

1. **Vehicle mobility normalization** First, we need to apply the *Data Cleaning* on the vehicle datasets. Then, based on *OpenStreetMap*, we extract all intersections (landmarks) and generate the *Roadmap with Intersections*. Finally, by mapping each position record to respective nearest intersection (in Euclidean distance), we represent a vehicle's mobility by a *Trajectory in Intersections*.
2. **Charging lane location candidate extraction** With the data from the first stage, we apply the *Vehicle Visit Frequency Quantization* and the *Vehicle Passing Speed Quantization* to generate the traffic attribute values for each intersection. Then, we apply the *Clustering & Sorting of the Intersections' Attribute Values* to extract the intersections with both high vehicle visit frequency and short required charging lane length.
3. **Charging lane location determination** We first use the lengths of the trajectories to build the *Kernel Density Estimator* (KDE), which is used to estimate the vehicles' traffic at different landmarks. Then we formulate an optimization problem to solve the wireless charging lane deployment problem, and its solution outputs the locations and lane lengths for *Optimal Deployment of Charging Lanes*.

IV. PERFORMANCE EVALUATION

We used our Shenzhen datasets to drive our experiments. We built a trace-driven simulator with Apache Spark 1.5.2 [7]. Since there are no previous methods that handle the wireless charging lane deployment in a road network, we created two methods to compare with *CatCharge*: random placement (denoted by *Random*), and a method that maximally covers traffic flows (denoted by *MaxFlow*) [8]. In simulation, the

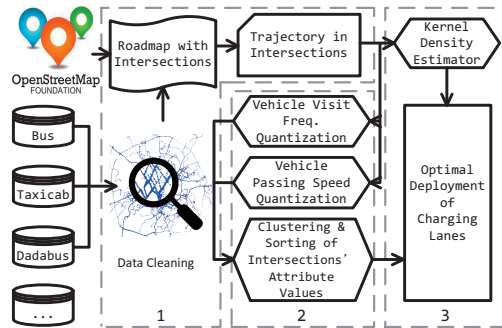


Fig. 4: Framework of *CatCharge*.

battery capacities of the EVs follow a uniform distribution ranging from 5kWh to 10kWh. We suppose every vehicle starts driving with full energy in battery at the beginning of a day. The energy supply rate of a charging lane is 150kW [1]. The unit price of a charging lane is \$100/m [1]. Since *Random* and *MaxFlow* do not have methods to determine the charging lane length, we suppose they deploy a 5km-long charging lane (maximum length in *CatCharge*) at each charging landmark, which can fully charge the EVs with the battery capacity smaller than 10kWh and the passing speed slower than 65km/h. For fair comparison, the deployment cost in *Random* and *MaxFlow* is the same as *CatCharge*. In *Random*, the locations for placing charging lanes are chosen randomly from the collection of landmarks. *MaxFlow* is for charging station deployment and we use it for charging lane deployment. We choose the landmark that covers the most traffic sequentially until the deployment cost is reached. *MaxFlow* is a traffic flow based method. Since traffic flow based methods can more accurately estimate the charging demands than the charging demand based methods [9], we do not include a charging demand based method for comparison.

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