

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

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## 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) has emerged as the next-generation solution for in-motion Electrical Vehicle charging.



**Dataset Analysis** 



How to deploy charging lanes in a metropolitan road network to minimize the deployment cost while enabling EVs' continuous operability?

- 1. Reducing charging lane length  $\rightarrow$ Vehicle velocity at charging lanes matters
- 2. Reducing the number of deployed charging lanes  $\rightarrow$  Vehicle visit frequency and multi-source vehicle traffic matter

Landmarks with both high vehicle visit frequency and slow passing speed are distributed over various regions.



# **Performance Evaluation**

- Evaluated with the Shenzhen trace on a trace-driven simulator with Apache Spark 1.5.2.
- Compared with Random and 2. MaxFlow [1]



Our goal: design a novel wireless charging lane deployment approach to support the continuous operation of EV traffic with the minimum deployment cost.

**Dataset Description** 

Shenzhen's vehicle records (e.g., timestamp, GPS position, speed, occupancy) for one month (July 1-July 31, 2015).

Taxicab Dataset. Mobility records of 15,610 taxicabs. The daily size of the uploaded data is around 2GB.

Vehicle visit frequency 10<sup>4</sup>

Landmarks vehicle with both low (60km/h) and high speed passing vehicle visit frequency (10<sup>4</sup>/day) take up a small portion within the square circle.



KDE can fit the distribution of trajectory length well, and can be used to infer the vehicles' probability of reaching each landmark in the road network

Result: CatCharge>MaxFlow>Random

#### **References**:

[1] W. Yao, J. Zhao, F. Wen, Z. Dong, Y. Xue, Y. Xu, and K. Meng, "A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems," TPS, 2014.

## **Future Work**

We plan to further consider human activities that affect the movement of public transit vehicles (e.g., pickup requests) in determining the deployment of charging lanes.

- 2. Bus Dataset. Mobility records of 14,262 buses (e.g., timestamp, GPS position).
- 3. Dada bus Dataset. A customized transit service, which consists of the status (e.g., timestamp, GPS position, speed) of 12,386 reserved service buses.
- 4. Road Map. The road map of Shenzhen is obtained from OpenStreetMap.



CatCharge consists of three stages:

- 1. Vehicle mobility normalization 2. Charging lane location candidate extraction
- 3. Charging lane location determination



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