Optimizing In-motion Wireless Charging Service Efficiency for Electric Vehicles: A Game Theoretic Approach

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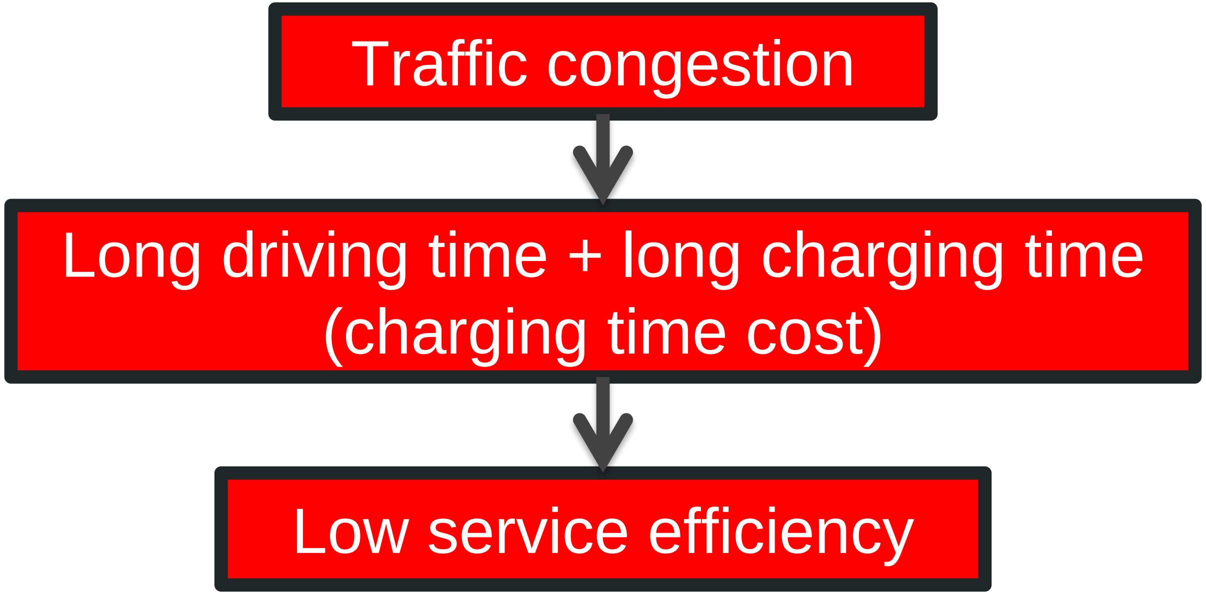
In-motion wireless charging

Potential solutions to the well-known range anxiety problem

Why traffic congestion should be avoided for in-motion wireless charging?



EV scheduling methods

IEEE TITS'16 IEEE TPS'13

IEEE TITS'15 IEVC'12

VIN'11 SEUCSG'10

CDC'10 POWERCON'10

Vehicle future mobility based routing

INFOCOM'11

IEEE TPDS'11

IEEE TMC'16

INFOCOM'11

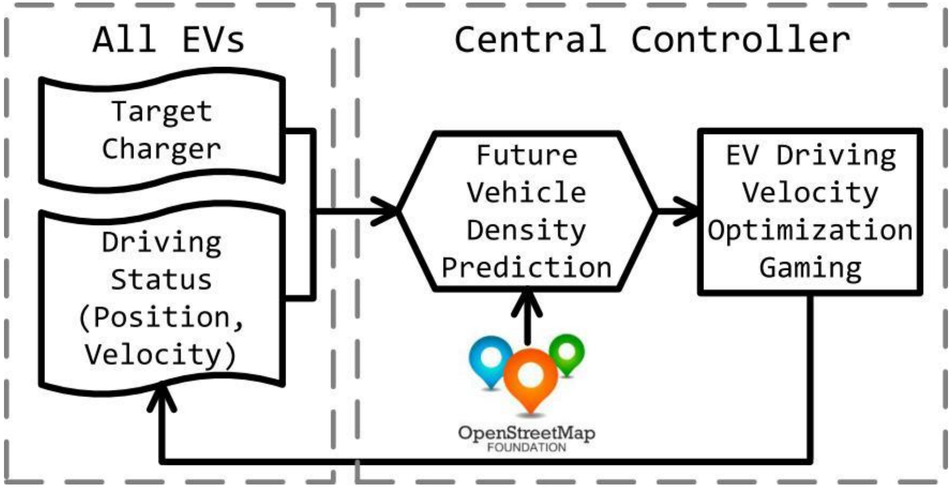
1

Not directly applicable for wireless chargers

2

Confirms trajectories can be used for estimating vehicle density

Proposed approach: WPT-Opt



A game theoretic approach for optimizing in-motion wireless charging service efficiency

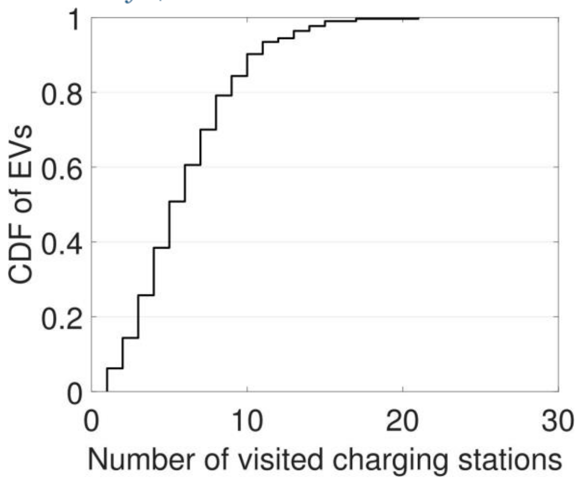
Overview

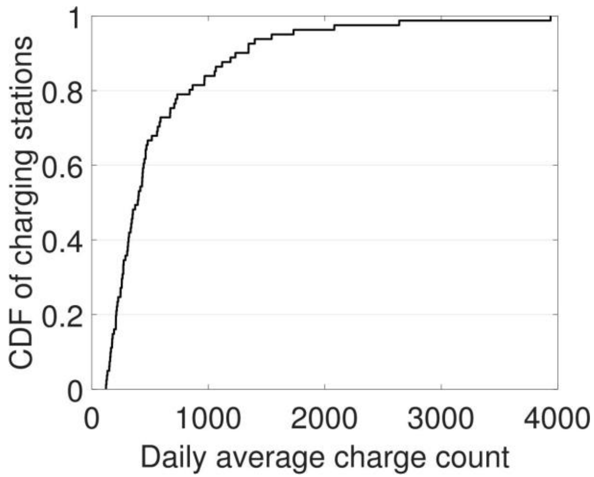
Metropolitan-scale dataset measurement

System design of WPT-Opt

Experimental results

Conclusion with future directions





EVs have quite stable preference in selecting charging stations

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congestion at preferred charging stations or the road segments to them

Charging stations have different levels of popularity among the EVs

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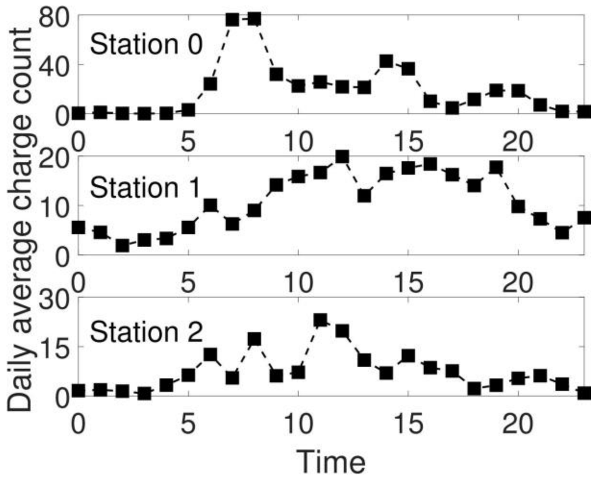
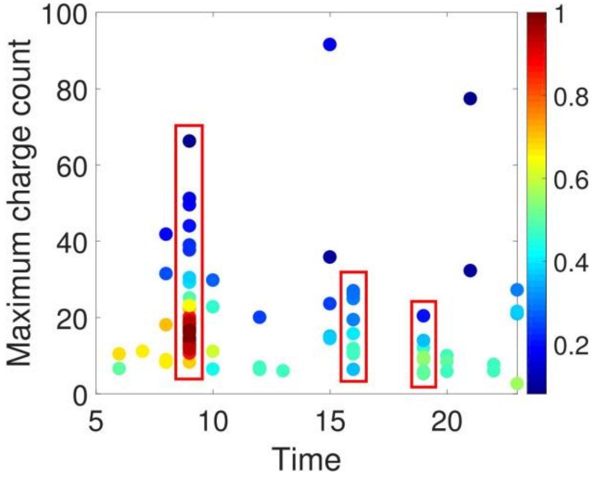
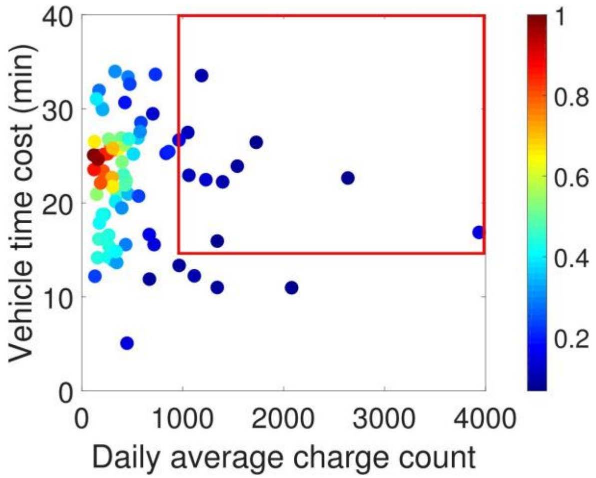
The competition of the EVs for popular charging stations must be avoided

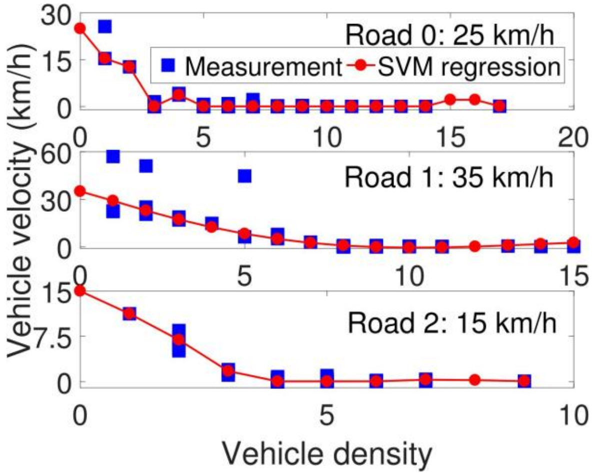




Busy charging times are quite different for different chargin stations

Most busy charging times happen at around 09:00, 16:00 and 19:00





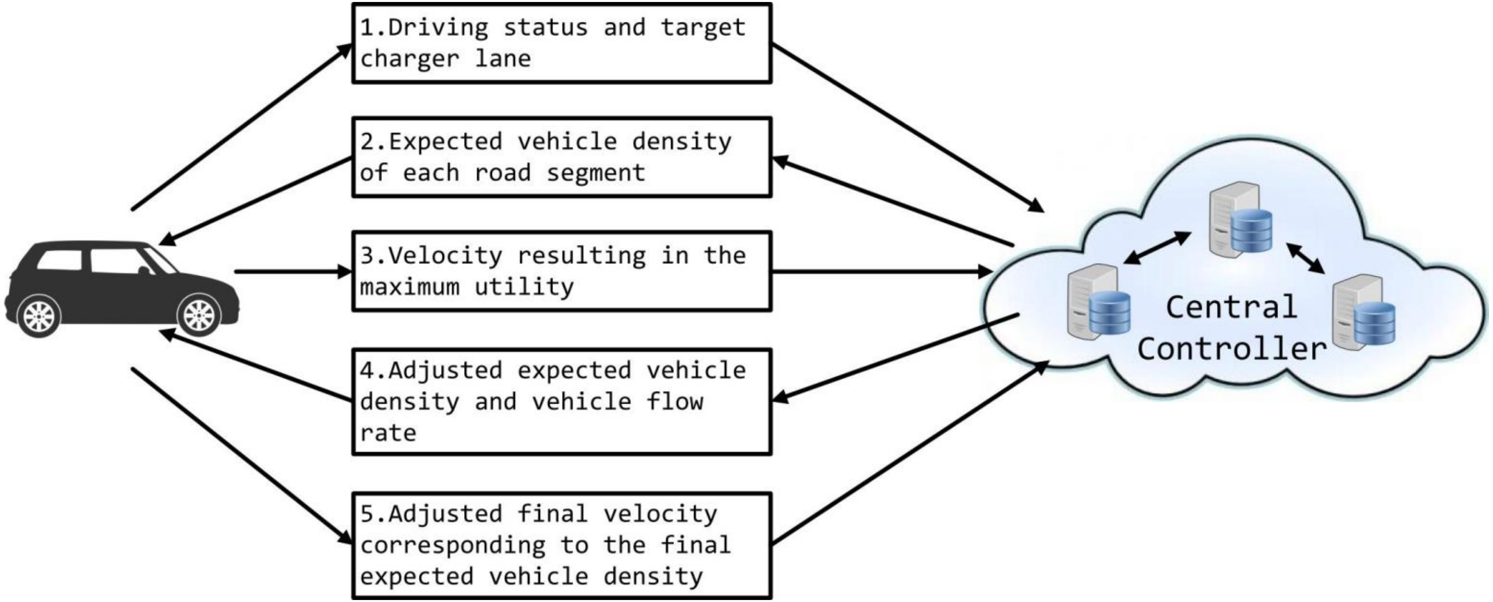
Charging stations in red square are frequently visited and result in long charging time cost

Competition for these charging stations exists

Relation between vehicle driving velocity and vehicle density of a road segment is non-parametric

Use Support Vector Machine Regression (SVMR) model to learn the relation function

Gaming process



Future vehicle density prediction

Problem 1: How to estimate the travel time to each road segment of an EV's future trajectory?

Problem 2: How to utilize the future trajectories and the travel times to the road segments to predict the future vehicle density of each road segment?

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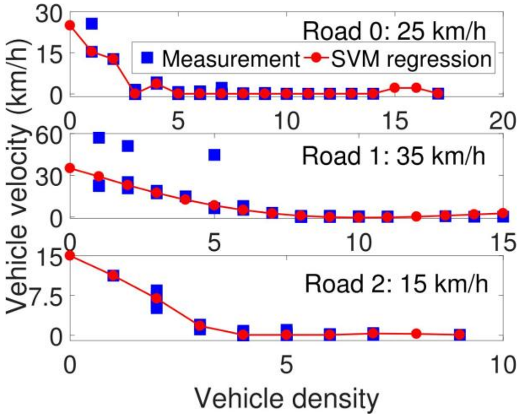


Use SVMR to model the relation

$$v_i = f_i(d_i)$$

Travel time of a single road segment:

$$\tilde{t}_k = l_k / v_k$$

Estimated total travel time to ith road segment:

$$\tilde{T}_i = \sum_{k=1}^{M_i} \tilde{t}_k$$

M_i is the #of road segments in the trajectory

Future vehicle density prediction

Problem 2: How to utilize the future trajectories and the travel times to the road segments to predict the future vehicle density of each road segment?

Travel times follow normal distribution, and are i.i.d.

For a road segment: $$d_{c+1}^{s_i} = \sum_{k=1}^{N} P_k(T_i \leq t_j^e - t_j^s)$$

N is the number of vehicles that will pass s_i during $\left[t_j^e, t_j^s\right]$

Utility of central controller:

$$L(d) = \sum_{i=1}^{N_s} d_i \cdot v_i + \sum_{i=1}^{N_e} d_i \cdot v_i \cdot e^{-|v_i - v_i^{'}|}$$

Utility of EV drivers:

$$F(v_i, \alpha_i) = \alpha_i \cdot \ln(v_i) - \frac{1}{1 + e^{-(v_i - f_i(d))}} dv_i$$

$$\text{s.t.} \quad v_i \leq v_i^{\max}$$

Optimal driving velocity selection

1. The central controller offers densities:

$$D = \{d_u\} = \ln(u+1) \cdot \bar{d}_{c+1},\ u \in [1, \ldots, n]$$

2. For each d_u , each EV chooses velocity by:

$$v_{iu} = \arg\max_{v_i \le v_i^{\max}} F(v_i, \alpha_i)$$

3. The central controller finalizes the expected vehicle density:

$$d_l = \arg\max_{d_u \in D} L(d_u) = \arg\max_{d_u \in D} d_u \sum_{N_S} v_{iu}$$

4. Each EV updates velocity according to the new vehicle density

Performance evaluation

Simulation settings:

- EV battery capacities range between 32 kWh and 37 kWh
- Charger lane positions follow the existing charging station positions
- Use SUMO to simulate 10,000 EVs on Shenzhen's road network for 24 hours
- An EV will seek recharge if its State-of-Charge (SoC) is lower than 20%

Comparison:

- Recommend (IEEE TITS'16),
  - Considers current occupancy of charging stations
  - Considers current traffic status on road segments
- Baseline
  - central controller always recommends the charger lane with the shortest driving time

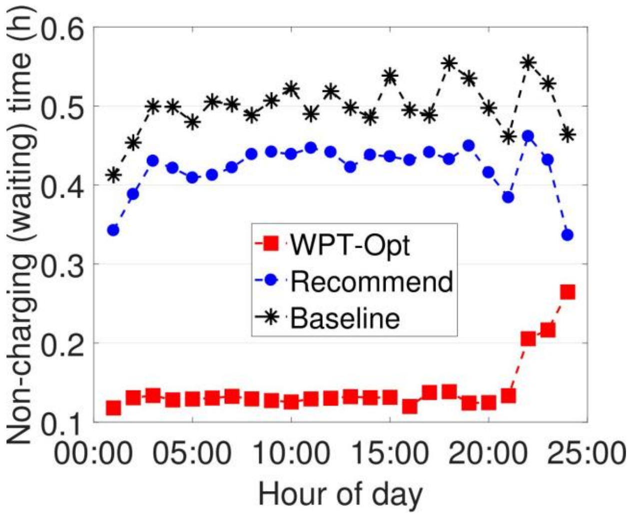
Performance evaluation (cont.)

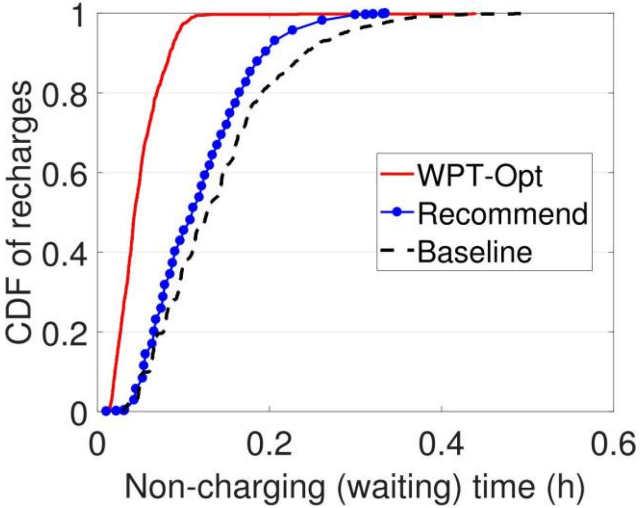
Evaluation metrics:

- Average non-charging time of EVs
- Average charger seeking time of Evs
- Average number of charged Evs
- Average vehicle flow rate of all road segments

Performance evaluation (cont.)

Average non-charging time of EVs

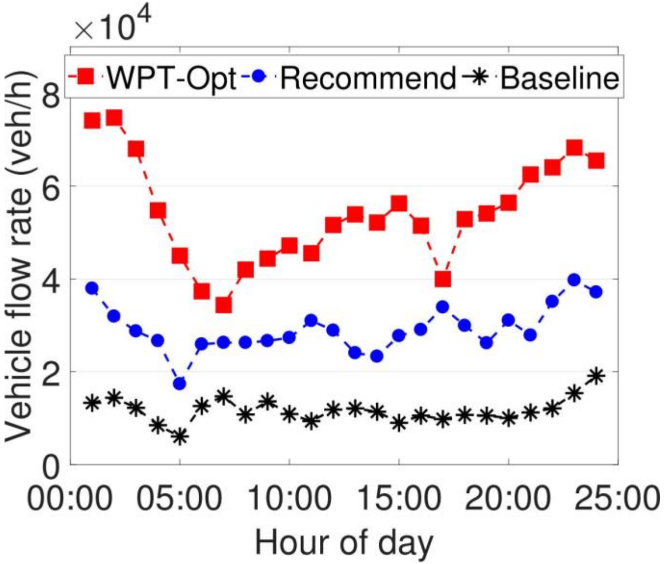




WPT-Opt<Recommend<Baseline

Performance evaluation (cont.)

Average vehicle flow rate of all road segments



WPT-Opt>Recommend>Baseline

Conclusions

1. EVs have spatial and temporal preference on selecting chargers, and such preferences can lead to competition for chargers.

2. The formulated non-cooperative Stackelberg game between EVs and a central controller can maximally reduce the average charging time cost of the EVs by approximately 200% over comparison methods.

3. In the future, we plan to consider more EV charging behavior factors (e.g., different charging time and target charger lane in weekday and weekend).

Thank you!
Questions & Comments?

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