A Commercial Charging-as-a-Service Platform for Emerging Mobile EV to EV Charging Service

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Introduction

The main challenge for the mass adoption of EVs is 'range anxiety'. Many proposed solutions, such as building dense charging stations, embedding wireless charging lanes, or battery swapping services, suffer from respective infrastructure investment and/or implementation difficulties [1][2][3][4][5]. Moreover, recent success of vehicle-to-vehicle charging technology enables dispatching mobile chargers to serve EVs at designated locations [12][13][14][15]. It saves prohibitive infrastructure investment, EVs' detours for charging, but not travel delay resulting from the long charging time. To completely address this issue, this study shares the common interests with existing studies [6][7][8] in developing mobile electric-vehicle-to-electric-vehicle charging (mE2) services enabled by the integration of CAV technology and vehicle-to-vehicle-charging technology. Briefly, CAVs cooperate their movement to allow electricity exchange between EVs while moving [8][9][10][11].

While the technical feasibility of this charging technique is confirmed, its implementation still faces many operation problems: in particular, how to quickly match the electricity provider (EPs) to electricity demands (EDs), and then efficiently route EPs to approach EDs, considering their mobility and traffic overhead. A pioneering study by Abdolmaleki et al. [8] tried the crowdsourcing approach. This approach may not be able to find enough volunteer EPs in the early market with a low EV penetration. This study, therefore, seeks to develop a commercial Charging-as-a-Service (CaaS) platform for cultivating mE2 charging service under a low EV penetration environment. The centralized platform collects EDs' charging requests and trip plans, and then optimally and timely dispatches EPs to serve EDs en route batch by batch, depending on the arriving service requests.

The main contributions of this study are summarized as follows. (i) Introduced the CaaS platform to help relieve EV range anxiety and cultivate usage of such emerging technology while EV penetration is low. (ii) Developed a novel VRP model to optimally dispatch EPs, factoring the unique feature of on-the-move electricity delivery (i.e., mE2-VRP). Both traffic overhead and service efficiency are considered in the modeling process. (iii) Developed a machine learning and parallel computation aided heuristic algorithm: Clustering-aided Clarke and Weight Savings (CCWS), to efficiently solve a large-scale mE2-VRP. It adapts the CaaS platform to online application in practice. (iv) Taking advantage of the merits of our approaches, we conduct numerical studies to explore insights and the applicability of such platform in citywide and statewide implementations. Overall, this study is among the early efforts to study the application of the mE2 charging technologies. It significantly contributes both theoretical methodology and practical applications to this emerging technology.

Methodology

Mathematically, we model the CaaS platform as a vehicle routing problem (i.e., mE2-VRP), which searches optimal solution for routing EPs to approach EDs to do on-the-move electricity deliveries so that the EDs can avoid detours and waiting delay, while minimizing the traffic overhead from the EPs. Specifically, the mE2-VRP is built upon a spatiotemporal network subjects to EP flow conservation, EDs' path plans, and safe energy constraints. We highlight the unique features of this VRP model as follows. They differentiate this study from existing relevant efforts and also present new modeling and solution challenges. First, the on-the-move electricity delivery requires a period of trip synchronization between a pair of EP and ED in a spatiotemporal space rather than a snapshot at static locations. Next, the CaaS allows an ED to be served by multiple EPs during its itinerary (i.e., partial charging is allowed at each service). To contain these features, the mE2-VRP is modeled as a large-scale integer program with a novel and effectiveness-proved subtour elimination constraint. Last, EDs may send the service requests en routes. To render such online application, we develop a clustering aided heuristic algorithm, CCWS, which can solve a large-scale mE2-

VRP with satisfying effectiveness. Mainly, the algorithm first strategically clusters the EDs into multiple groups so that the EDs in each cluster can be independently served by the EPs. In this way, we decompose a large-scale master problem (i.e., mE2-VRP) into a number of small sub-problems (i.e., sub-mE2-VRPs). Next, we solve each sub-mE2-VRP by parallel computing and obtain the seed tours for the EPs. The seed tours are further merged over all clusters to explore a better solution for the master mE2-VRP. The equivalence of the merging rules and the corresponding constraints in mE2-VRP is mathematically proved to ensure the feasibility of the heuristic solutions.

Main Results

We conduct experiments on the Chicago sketch network and Florida statewide network with field O-D trip data to simulate ED trips, aiming to evaluate the computation performance of the CCWS algorithm, examine the traffic impacts of the CaaS, and analyze the sensitivity of the CaaS service efficiency to input parameters.

The results in Table 1 show that the CCWS can solve mE2-VRP up to 10,000 number of EDs in a city network within a realistic computation time (~700s). It outperforms Gurobi when the instance size is larger than 100 EDs. Moreover, the CCWS provides a comparable/better solution (fleet size) to/than that found

Table 1: *Computation performance of CCWS algorithm*

Instance size	*Gurobi*		*CCWS*	
	Solution (1h)	*Solution (2h)*	*Solution*	*Solution time/s*
60	14	14	14	6.02
80	20	19	20	6.23
100	26	24	24	7.20
120	-	-	24	8.50
140	-	-	26	9.52
200	-	-	32	12.59
300	-	-	47	17.50
600	-	-	88	30.66
1,200	-	-	182	54.91
2,000	-	-	289	107.50
4,000	-	-	589	196.78
6,000	-	-	948	374.86
8,000	-	-	1,211	536.93
10,000	-	-	1,524	691.64

by Gurobi within two hours. The super performance of the CCWS algorithm enables this study to further explore the systematic impact and performance of the CaaS platform in real-world settings with large-scale instances.

Figure 1 (a)-(c) demonstrates the traffic impacts of the CaaS platform under different EV penetration and initial traffic congestion levels (v/c ratios). The results indicate that to serve all EDs, the CaaS platform will lead to a 15% system travel time increase (under which we consider insignificant) when the EV penetration is 55%, 15%, and 10% in a light, medium, and heavy traffic congestion environment, respectively. These results imply that the CaaS platform is especially suitable for the low EV penetration environment. Together with Figure 1(d), we conclude that the CaaS platform is applicable globally in the next few decades.

Moreover, the sensitivity analyses indicate that to maintain a high service efficiency, the CaaS may ensure the initial energy inventory of EPs above 130 kWh to avoid frequent recharging trips. More importantly, the CaaS platform may lead to less traffic overhead if the majority of EDs are served when they are under lower energy shortage. Last, our experiments indicate that the CaaS platform performs better for the EDs with shorter intercity trips than those conducting longer statewide trips. Overall, these results suggest doing congestion pricing according to EDs' energy request and trip length to balance the service quality, operation cost, and system traffic impacts.

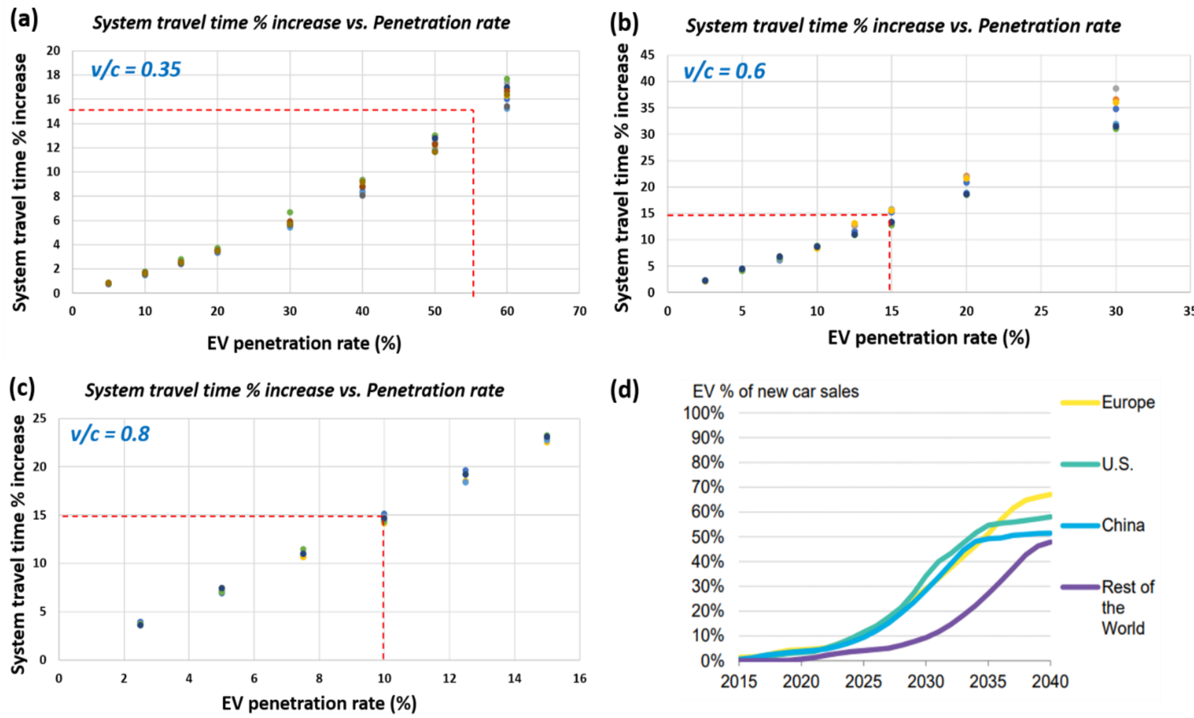

Figure 1. System travel time percent increase and EV penetration rate relationship under three scenarios: (a) low or no congestion, around 102,000 background EV trips; (b) moderate congestion, around 173,000 background EV trips; (c) heavy congestion, around 231,000 backgroud EV trips. And (d) long-term EV sales penetration prediction by country (Source: Bloomberg New Energy Finance)

Conclusion

This study introduces the CaaS platform as an innovative and promising solution to address the range anxiety problem towards the low EV penetration market. To secure low systematic traffic impacts and high service efficiency of the CaaS platform, the study contributes a new mE2-VRP model and a CCWS heuristic algorithm to efficiently provide high-quality routing solutions for dispatching EPs even under a large-scale instance in reality. Numerical experiments using field dataset from Chicago and the state of Florida suggest that this CaaS platform leads to minor extra traffic in a low EV penetration environment, thus it is a promising solution to cultivate the EV massive usage in the future without significant infrastructure investment. Moreover, the CaaS platform can achieve a high service efficiency by leveraging the energy inventory control of fleet and pricing strategy towards EDs' energy shortage rate and trip length.

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