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An optimal charging station location model with the consideration of electric vehicle's driving range

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ABSTRACT

Reasonable charging station positions are critical to prompt the widespread use of electric vehicles (EVs). This paper proposes a bi-level programming model with the consideration of EV's driving range, for finding the optimal locations of charging stations. In this model, the upper level is to optimize the position of charging stations so as to maximize the path flows that use the charging stations, while the user equilibrium of route choice with the EV's driving range constraint is formulated in the lower level. In order to find the optimal solution of the model efficiently, we reformulate the proposed model as a single-level mathematical program and further linearize it in designing the heuristic algorithm. The model validity is demonstrated with numerical examples on two test networks. It is shown that the vehicle's driving range has a great influence on the optimal charging station locations.

1. Introduction

Traffic emission, especially road-based transport emission, has caused serious environmental pollution, which is harmful to our health. The automobile exhaust may result in atmospheric pollution, such as fog and haze, which has attracted the attention of most people. A promising way to reduce automobile exhaust is using EVs instead of internal combustion vehicles. However, the EVs' limited driving range and the insufficient charging stations have restricted the widespread adoption of EVs. It is imperative to construct sufficient number of charging stations for attracting private vehicle drivers to use EVs. A limited number of studies are carried out to investigate the optimal location of charging stations. With the development of new technology, more data are available easily and accurately. Cai et al. (2014), Shahraki et al. (2015) and Tu et al. (2016) used the trajectory data, especially the taxi's Global Position System (GPS) data, to locate the charging stations. Dong et al. (2014) applied the GPS data from the conventional gasoline vehicles to represent the real world EV travel activities, proposed an activity-based assessment method to evaluate EV feasibility in the real world driving context, and applied the genetic algorithm to find optimal locations for public charging stations. Huang and Zhou (2015) utilized the average national data to study the allocation of charging resources to satisfy charging demand for a workplace. Yang et al. (2016) designed and implemented a Stated Preference (SP) Survey to analyze the battery EV drivers' charging and rout choice behaviors. He et al. (2016) used aggregate data from municipal statistical yearbooks and the national census to estimate the EV demand, and compared the optimal locations from three different facility location models. Yang et al. (2017) applied a large-scale GPS trajectory data collected from the taxi fleet to allocate chargers for battery EV taxis, and investigated the tradeoff

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between installing more chargers versus providing more waiting spaces. Xu et al. (2017) utilized the GPS location information and charging information of battery EVs in Japan to investigate the choice for charging mode and location, identified an appropriate instrumental variable to solve the endogeneity issue in the mixed logit model, and provided some useful insights in the operation strategy for public charging stations. Xylia et al. (2017) used the data of 143 routes and 403 existing bus stops in Stockholm to analyze the electrification of the bus network, and revealed that the lower operational costs and fuel prices for electric buses can balance the high investment costs for charging infrastructure. The above data-driven charging station location models are suitable for electric taxi and electric bus, but the models are not applicable for private vehicles due to the limited private vehicles' GPS data. Therefore, researchers use traffic demand data between origin-destination (OD) pairs as the basic resource of the charging demand and formulate mathematical programming models to study the impacts of some factors on optimal charging station locations. Jung et al. (2014) studied the influences of queuing delay on the optimal location of charging stations. He et al. (2015) found that, if drivers simultaneously determine the whole trip chain paths and the charging plans, they might save time compared with determining the minimum path time and charging plan separately. Riemann et al. (2015) combined the flow-capturing location model with the stochastic user equilibrium model to deploy the wireless charging infrastructure. Wang et al. (2016b) investigated the efficient solution methods for a distance-constrained traffic assignment problem with trip chains embedded in equilibrium network flows. Li et al. (2016) proposed a multi-period multipath refueling location model to determine the cost-effective public EV charging station rollout scheme on both spatial and temporal dimensions. Guo et al. (2016) analyzed business-driven EV charging infrastructure investment planning, and proposed a network-based multi-agent optimization modeling framework to study the competition among different public charging suppliers. Ghamami et al. (2016) used a general corridor model to minimize the total system cost in configuring plug-in EV charging infrastructure, and proposed a modified model with consideration of the flow-dependent charging delay induced by congestion. Fuller (2016) proposed an optimization model to deploy the dynamic charging infrastructure, and found that dynamic charging can be a cost effective approach to extending driving range. Chen et al. (2017) investigated the deployment of charging lanes and charging stations along a long traffic corridor, discussed the tradeoff between the charging delay caused by stopping at charging stations and the higher charging price caused by additional devices to enable charging-while-driving, and found that charging lanes were economically viable and competitive for attracting drivers. Liu and Wang (2017) developed a model with multiple types of EV recharging facilities to minimize the public social cost, and used the efficient surface response approximation algorithm to solve the complex tri-level programming problem. The above models can deploy the locations of charging stations or wireless charging lanes, but they do not precisely compute the benefit of charging stations since charging at home and charging en-route are not simultaneously considered in these models. An optimal location of charging stations should be able to capture the maximum flow using the stations. This means after a long term development of charging stations, the optimal location of charging stations should attract sufficient flows to use the charging facilities. However, the flows captured by charging stations do not mean these flows need to use the public charging facilities because many EVs may be charged at home as well. Therefore, we use the maximum flow that can utilize charging stations en-route as the optimization objective in this paper.

Some investigations are made on the influences of limited driving range on optimal location of refueling facilities for alternative-fuel vehicles. Kuby and Lim (2005) formulated a flow refueling location model on a network so as to maximize the total flow volume refueled. Because of the limited driving range, the network vertices do not constitute a finite dominating set, Kuby and Lim (2007) then considered the arc segments where a single facility could refuel a path that would otherwise need two facilities at vertices to refuel. Upchurch et al. (2009) studied the impacts of refueling station capacity on station location. To improve the computational efficiency on large networks, Lim and Kuby (2010) developed three heuristic algorithms for locating alternative-fuel stations. What's more, based on the covered links, Capar et al. (2013) presented a new formulation of the flow refueling location model and a more computationally efficient algorithm. Kim and Kuby (2013) observed that drivers may change from a shortest path to others containing refueling facilities and, proposed an artificial feasible network-based algorithm to enhance the computational efficiency. Li and Huang (2014) developed two heuristic methods to solve the multipath refueling location model in which each OD pair has at least one feasible path. The link congestion effect was not considered in the above models, so they cannot deal with the charging station location problem in urban network. Zhang et al. (2017) extended the works by Upchurch et al. (2009) and Capar et al. (2013), through incorporating demand dynamics to the multi-period, capacitated, flow refueling model for optimizing the location of charging stations. The previous researches can decide relatively reasonable locations of charging stations, but they seldom discuss the impacts of charging stations on driver's route choice behavior. An exception is the research in Riemann et al. (2015), but this approach only deals with wireless charging without considering charging time and the model cannot ensure that there are no EV flows on infeasible paths (i.e., the lengths of these paths exceed the driving range). When a charging station is constructed, the set of feasible paths might change accordingly and immediately due to the driving range limitation, then some drivers may change their route choices which may finally change the flow pattern and in turn influence the location of other charging stations to be constructed. In this paper, we propose a bi-level model to find the optimal positions of all charging stations, through taking into account the driving range limitation and the charging time required in deploying these stations. We then reformulate the proposed model as a single-level model and linearize it in designing an efficient solution algorithm. Furthermore, we consider the situation in which some EV drivers probably charge at home, thus the maximum flows that charge en-route is regarded as the model objective. Compared with the existing studies, this paper's innovative work mainly manifests in the following aspects: (1) the complex relationship between the feasibility of a travel path and the distribution of charging stations is simplified under some reasonable assumptions, so that the linear equalities and inequalities are useful for describing this relationship; (2) the interaction between charging station constructors and travelers is explicitly formulated by a bi-level model in which flow-refueling location, route choice, en-route charging time and charging at home are all taken into account; (3) the proposed bi-level model is reformulated as a single-level model, in which a new Log model is used to significantly reduce the number of binary variables so as to enhance the computational efficiency of solution