Transportation Research Part B 117 (2018) 431–454

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

# Modeling electric vehicles adoption for urban commute trips

Xuekai Cen, Hong K. Lo*, Lu Li, Enoch Lee

*Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, China*

ARTICLE INFO

*Article history:*
Received 26 September 2017
Revised 4 September 2018
Accepted 4 September 2018

*Keywords:*
Charging stations
Electric vehicles
Mixed user equilibrium
Charging ratio

ABSTRACT

In this paper, a mixed user equilibrium (MUE) model with Electric Vehicles (EVs) and Gasoline Vehicles (GVs) is proposed to account for the charging behavior of EVs in an urban network. The main difference between EVs and GVs lies in that certain EVs with immediate charging need have to traverse a specific station for recharging, while GVs and other EVs without immediate charging need do not have such a requirement. The proportion of EVs with immediate charging need, referred to as charging ratio in this study, is an OD specific endogenous variable, related to their daily commute trip lengths and EV driving ranges, i.e., EVs will need recharging once every few days. The MUE conditions state that EVs with charging need choose the routes via a charging station while en route to their destinations with minimum travel time cost, electricity cost plus charging station cost; whereas GVs and EVs without charging need select the routes with minimum travel cost without having to traverse any charging station. This study also captures the interaction between network design (such as charging station locations) and EV demand which follows a logit model calibrated with an EV market survey conducted in Hong Kong. We formulate the MUE problem first with a nonlinear complementarity (NCP) approach and solve it with a gap function, then we relax the charging ratio to be exogenous and formulate a convex mathematical program for efficient solutions, with the charging ratio iteratively determined. Furthermore, we observe that the resultant link flows exhibit the property of link flow preservation, i.e., the total link flows remain unchanged under a range of EV and GV demands. We first solve the Yang-Bell network to demonstrate its properties, and then solve the Sioux-Falls network to show its solution efficiency.



## 1. Introduction

The transportation sector adds substantially to greenhouse gas (GHG) emissions, for instance, about 28% in the United States, much of which can be attributed to its heavy reliance on fossil fuels. Electric vehicles (EVs) are therefore proposed as one major contender to reduce emissions from the transportation sector, and have enjoyed fast growth in recent years. However, massive adoption of EVs encounters major obstacles, namely high purchase price, limited driving range, long battery charging time and insufficient charging infrastructure (e.g., He et al., 2013, 2014; Nie and Ghamami, 2013). Therefore, to encourage the adoption of EVs, governments usually have two options, i.e., subsidize their purchase prices and/or facilitate charging stations deployment.

Investigating the impact of purchase price subsidy of EVs calls for a behavioral model to predict consumers' vehicle choices. There is a vast literature on vehicle choice models based on various discrete choice approaches (e.g., Xu et al., 2017b; Potogou and Kanaroglou, 2007; Javid and Nejat, 2017). Previous studies indicated that the choice between EVs and conventional vehicles is influenced by vehicle attributes (purchase price, driving range, operating cost, safety), fuel price,

* Corresponding author.
*E-mail address:* cehklo@ust.hk (H.K. Lo).

https://doi.org/10.1016/j.trb.2018.09.003

and drivers' socio-economic attributes. Typically vehicle choice models are formulated via multinomial logit (MNL) or nested multinomial logit (NMNL) approaches and calibrated by stated preference surveys. The feedback from network design, such as placement of charging stations, are often left out or considered exogenously. In fact, the network design (e.g., charging station locations) will affect the EV demand, as demonstrated in Liu and Wang (2017) and Nie et al. (2016), where vehicle choice models are incorporated to decide charging locations and optimal incentive policies.

The deployment of charging stations needs to address the range anxiety of EVs, or the anxiety that the battery would run out while en route, which affects EVs' route choices and hinders their widespread adoption. Besides the capacity of the EV battery, range anxiety can be attributed to the limited charging stations in the transportation network. Understandably, range anxiety arises in inter-city long-distance trips that exceed the EV driving range. But for inner-urban commute trips this study sets out to investigate, it is more about the inconvenience of having to charge or refuel more frequently, perhaps once every few days, as compared with GVs, and the detour needed for recharge in the presence of limited charging stations (Worley and Klabjan, 2011). That is, the range anxiety of urban EV drivers is mostly due to the scarcity of charging stations with comparatively long charging time.

Anticipating the EV charging time will be reduced by battery swapping scheme (Adler and Mirchandani, 2014) or quick charging stations, the crux to jumpstart the EV market in an urban area hinges on the widespread deployment of quick charging or BS stations. In an urban setting, range anxiety is mainly related to the difficulty of finding a charging station when needed, which can be obliterated with the growth in number of charging stations, analogous to gas stations. Both EVs and GVs will coexist in the urban network for a long period, considering the horizon needed to build up a sufficiently dense charging infrastructure. In this paper, we propose a mixed user equilibrium (MUE) model with EVs and GVs, which share the same network and hence congestion. We investigate the charging behavior of EVs and determine the EV market penetration through a logit-based demand model with data collected from a stated-preference survey in Hong Kong.

Range anxiety, the inherent difference between EVs and GVs, was identified early on to be an issue for investigation. Kuby and Lim (2005) developed a flow-refueling location model (FRLM) to ensure that vehicles always get a chance to be recharged before their batteries deplete in long trips. For the same purpose, Wang and Lin (2009) proposed refueling logistics of alternative-fuel vehicles, and formulated a linear program to minimize the total construction cost of stations, which was extended by Wang (2011) and Wang and Lin (2013). The above studies assumed that EVs choose fixed shortest paths, leaving out the effect of congestion on their route choice behavior. Zhang et al. (2017) extended the FRLM to develop a multi-period capacitated flow refueling location model while considering EV demand dynamics and charging availability. Besides range anxiety, there are many recent studies on EVs, such as optimal deployment of charging stations without considering UE (e.g., Mak et al., 2013; Nie and Ghamami, 2013; Li et al., 2016; Ghamami et al., 2016), optimal deployment of wireless charging lanes (e.g., Liu and Wang, 2017; Chen et al., 2016, 2017), EV routing and scheduling problems (e.g., Kang and Recker, 2014; Liao et al., 2016; Adler et al., 2016; Adler and Mirchandani, 2014; Schneider et al., 2014; Xi et al., 2013; Jung et al., 2014). Since our study is about EV charging behavior under a mixed user equilibrium of EVs and GVs, the literature review below only focuses on UE-based formulations, and a review of EV network modeling approaches can be found in Jing et al. (2016).

He et al. (2013) developed an equilibrium framework to capture the interaction among charging opportunities, electricity prices, and destination and route choices of plug-in hybrid electric vehicles. They investigated the optimal deployment of charging stations to maximize social welfare associated with both transportation and power networks. The network equilibrium models of EVs considering the driving range and flow-dependent energy consumption were further studied by He et al. (2014). In that paper, an EV model under UE considering recharging time and flow dependency of energy consumption was investigated, and an iterative algorithm to solve the model was developed. He et al. (2015) further proposed a tour-based EV network equilibrium model, considering drivers' adjustments and interaction of travel and recharging decisions to optimally locate charging stations. The above studies assume all vehicles were EVs, without considering the interaction between EVs and GVs. On the other hand, a user equilibrium model of mixed traffic flow was formulated in Jiang et al. (2014) and Jiang and Xie (2014), where drivers chose their destinations to minimize their individual travel times, parking times and costs. Range anxiety was formulated to be a linear constraint to exclude infeasible EV paths, and different types of charging infrastructure were located at destinations with different parking costs, without considering the impact of charging time of EVs in the UE formulation. Recently, Xu et al. (2017a) developed a UE model considering mixed GVs and EVs subject to battery swapping and road grade constraints. The model considered fixed EV demands by OD pair, wherein EVs minimize their individual path costs and charging costs, and GVs minimize their individual path costs without considering the difference between fuel and electricity costs. The modal split between EVs and GVs was fixed in the model. The driving range of EVs is incorporated by implementing a driving range constraint to sort out their feasible paths, which were then generated for traffic assignment. The resultant minimization program is convex in link flows and station swapping flows, and solved by a Frank-Wolfe based algorithm.

For the context of inner-urban commute trips, the current driving ranges of EVs are typically sufficient to cover the daily requirements. For example, the daily average commute distances of London and Sydney are, respectively, 13.8 km (Gomm and Wengraf, 2013) and 15 km (Australian Government, 2015). We, therefore, put forward the concept of charging ratio to capture the effect of the limited driving range on EVs. We divide EVs into two categories: those with immediate charging need and hence must traverse a charging station for recharging, and those without such a need and they behave similarly to GVs, except for their different route choices due to the cost difference between fuel price and electricity price. The frequency of EVs with charging need is related to the commute distance and the driving range of EVs. For example, EVs