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Improving the electrification rate of the vehicle miles traveled in Beijing: A data-driven approach

Meng Li [a], Yinghao Jia [b], Zuojun Shen [c,d,b], Fang He [b,*]

[a] *Department of Civil Engineering, Tsinghua University, Beijing 100084, PR China*
[b] *Department of Industrial Engineering, Tsinghua University, Beijing 100084, PR China*
[c] *Department of Civil and Environmental Engineering, University of California Berkeley, Berkeley, CA 94720, United States*
[d] *Department of Industrial Engineering and Operations Research, University of California Berkeley, Berkeley, CA 94720, United States*

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ABSTRACT

Electric vehicles (EV) are promoted as a foreseeable future vehicle technology to reduce dependence on fossil fuels and greenhouse gas emissions associated with conventional vehicles. This paper proposes a data-driven approach to improving the electrification rate of the vehicle miles traveled (VMT) by taxi fleet in Beijing. Specifically, based on the gathered real-time vehicle trajectory data of 46,765 taxis in Beijing, we conduct time-series simulations to derive insights for the public charging station deployment plan, including the locations of public charging stations, the number of chargers at each station and their types. The proposed simulation model defines the electric vehicle charging opportunity from the aspects of time window, charging demand and charger availability, and further incorporates the heterogeneous travel patterns of individual vehicles. Although this study only examines one type of fleet in a specific city, the methodological framework is readily applicable to other cities and types of fleet with similar dataset available, and the analysis results contribute to our understanding on electric vehicle's charging behavior. Simulation results indicate that: (i) locating public charging stations to the clustered charging time windows is a superior strategy to increase the electrification rate of VMT; (ii) deploying 500 public stations (each includes 30 slow chargers) can electrify 170 million VMT in Beijing in two months, if EV's battery range is 80km and home charging is available; (iii) appropriately combining slow and fast chargers in public charging stations contributes to the electrification rate; (iv) breaking the charging stations into smaller ones and spatially distributing them will increase the electrification rate of VMT; (v) feeding the information of availability of chargers in charging stations to drivers can increase the electrification rate of VMT; (vi) the impact of stochasticity embedded in the trajectory data can be significantly mitigated by adopting the dataset covering a longer period.

1. Introduction

Electric vehicles (EV) have drawn great attention in recent years because of the concern of traffic emissions and petroleum dependence (Krupa et al., 2014; Karplus et al., 2010). EVs include battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). Loosely speaking, BEVs incorporate a large on-board battery, which can be charged via a cord to

* Corresponding author.
E-mail address: fanghe@tsinghua.edu.cn (F. He).

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a power grid, and the battery provides energy for an electric motor to propel the vehicle. Besides the electric motor, PHEVs are also equipped with an internal combustion engine generator that provides electricity to the motor once the initial battery charge is almost exhausted. Almost all major vehicle manufactures have their EV models available in the market, and a fast-growing adoption of EVs is expected (Querini and Benetto, 2014). For example, China hopes the accumulated sale volume of BEVs and PHEVs will reach five million by 2020 (China State Council, 2012). However, there still exist several bottlenecks blocking the rapid development of EVs, such as high cost of EV battery, lack of charging infrastructure and shortage of battery range. Moreover, it's currently difficult for EV market to conquer all the obstacles only by itself. Considering the environmental benefits brought by EVs, many government agencies provide incentive policies, such as offering purchase subsidies and deploying public charging infrastructure, to promote the deployment of EVs (He et al., 2015; Motavalli, 2010; GLOBLE-Net, 2012).

To assist policy makers to optimally deploy public charging infrastructure, various approaches have been proposed in the literature.[1] The flow-capturing models locate charging stations to maximize the amount of travelers whose paths pass by at least one station (e.g., Hodgson, 1990; Berman et al., 1992, 1995; Hodgson and Berman, 1997; Shukla et al., 2011). Another approach optimizes the locations of public charging stations to maximize the social welfare, based on the network equilibrium that captures the EV drivers' spontaneous adjustments to the charging station deployment and interactions of travel and recharging decisions (e.g., He et al., 2013a, 2013b, 2013c, 2015; Jiang et al., 2012; Jiang and Xie, 2014; Chen et al., 2016). However, both above approaches need to make assumption of EV drivers' behavior, which remains to be verified by the real-world data. Recently, real-world driving profiles have been utilized to represent the drivers' travel pattern, estimate their public charging needs and then determine the station locations (e.g., Dong et al., 2013; Andrews et al., 2012; Dong and Lin, 2012). Nevertheless, due to the limited sample size of driving profiles (the sample size is often in the hundreds), it is difficult to provide conclusions at the city level based on the results of these studies (Cai and Xu, 2013).

Using the large-scale trajectory data of 11,880 taxis in Beijing, Cai et al. (2014) conducted simulation to explore how to locate public charging stations among the existing gas stations of Beijing. The electrification rate, defined as the ratio of miles PHEVs travel in all-electric mode over the total driving miles, is adopted to evaluate different location plans. The simulation results show that the total number of parking events or average parking vehicle-hour per day serves as a good criterion to locate charging stations. Utilizing the real-time and large-scale trajectory data to reveal the inherent heterogeneity of individual travel patterns, their research is among the first attempts to apply the "big data" mining techniques to the deployment of public charging stations for PHEVs.

Inspired by the above study and in order to reveal the travel patterns of individual drivers, this paper gathers the real-time vehicle trajectory data of 46,765 taxis in Beijing from October 1 to November 30 in 2014. Note that it is very likely that public fleets, such as taxis and buses, adopt EVs early. Applying the 'big data" mining techniques, we simulate drivers' travel and recharging behavior to quantitatively depict the relationship among the electrification rate of vehicle miles traveled (VMT) by PHEVs, battery range of PHEV and public charging station deployment plan. In order to improve the electrification rate of VMT and based on the simulation results, we further provide policy guidelines for the public charging infrastructure deployment planning, including the locations of public charging stations, the number of chargers at each station and their types. Compared to Cai et al. (2014), our paper's contribution lies in the following three aspects. Firstly, we consider the number of chargers at each public charging station is limited and hence PHEVs can charge batteries only if there are still unoccupied chargers left at stations. Therefore, our simulations are capable of accurately modeling the real-time operations of public charging stations and reflecting the interactions of different PHEVs' charging behavior. Note that considering the impact of public charging stations' limited capacity will inevitably cause great computational challenge especially for our case with 46,765 taxis. However, it is necessary for accurately estimating the electrification rate of VMT because recharging PHEV battery is time-consuming and the time PHEVs choose for recharging has a large degree of overlap. Secondly, based on the proposed simulation framework, we further quantify the contribution of introducing the intelligent charging guidance system for improving the electrification rate of VMT in Beijing. This analysis can offer insight for the development of "smart charging" program that is devoted to applying the information technology to improving the utilization efficiency of public charging stations in the future. Thirdly, this paper validates the dataset through addressing the stochasticity embedded in the vehicle trajectories among different days. Note that although this paper only examines one type of fleet in a specific city, the proposed data-driven approach is readily applicable to other cities and types of fleet with similar dataset available.

For the remainder of this paper, Section 2 introduces the dataset and provides the time-series simulation model. In Section 3, different simulation results are analyzed to derive insights for the deployment of public charging stations, and the dataset is also validated. Section 4 concludes the paper.

2. Data and time-series simulation model

Using Beijing as a case study and assuming the travel behavior of drivers remains unchanged after adopting PHEVs, we utilize the vehicle trajectory data of 46,765 taxis to characterize the heterogonous travel patterns of individual PHEV drivers. It is reported that Beijing plans to deploy 170,000 EVs on roads and build 10,000 fast chargers by 2017 (XinhuaNet, 2014). On

[1] For a more detailed review of the literature on the public charging station deployment, see He (2014).