Transportation Research Part D 41 (2015) 165–176

Contents lists available at ScienceDirect

Transportation Research Part D

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

Optimal locations of electric public charging stations using real world vehicle travel patterns

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ARTICLE INFO

Article history:

Keywords:
Optimization
Electric vehicles
Vehicle trajectory
Charging infrastructure planning

ABSTRACT

We propose an optimization model based on vehicle travel patterns to capture public charging demand and select the locations of public charging stations to maximize the amount of vehicle-miles-traveled (VMT) being electrified. The formulated model is applied to Beijing, China as a case study using vehicle trajectory data of 11,880 taxis over a period of three weeks. The mathematical problem is formulated in GAMS modeling environment and Cplex optimizer is used to find the optimal solutions. Formulating mathematical model properly, input data transformation, and Cplex option adjustment are considered for accommodating large-scale data. We show that, compared to the 40 existing public charging stations, the 40 optimal ones selected by the model can increase electrified fleet VMT by 59% and 88% for slow and fast charging, respectively. Charging demand for the taxi fleet concentrates in the inner city. When the total number of charging stations increase, the locations of the optimal stations expand outward from the inner city. While more charging stations increase the electrified fleet VMT, the marginal gain diminishes quickly regardless of charging speed.

Introduction

Fossil fuel-based road transportation has instigated increasing global demand for oil and air pollution, especially in urban areas (Hoogma et al., 2005). Emerging vehicle technologies that can utilize alternative fuels are considered as potential solutions for these issues, such as electric vehicles (EVs). Although the life cycle environmental implications of EVs depends on the fuel mix of electricity generation (Torchio and Santarelli, 2010), using electricity instead of liquid fossil-based fuels for road transportation can relocate tailpipe emissions from mobile vehicular sources to stack emissions at power plants which are more concentrated and easier to control. Many countries have set goals for EV adoption. For example, the U.S. plans to have more than 1.8 million plug-in hybrid electric vehicles (PHEVs); and China hopes to put 5 million hybrid and electric vehicles on the road by 2020 (Deutsche Bank Group, 2012; Navigant Research Group, 2013).

One of the factors that significantly impact the growth of the EV market is access to public charging infrastructure (Morrow, 2008). Many governments are investing in the deployment of public charging stations. For example, California has announced to build 200 public fast-charging stations; and British Columbia, Canada has set goals for building 570

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http://dx.doi.org/10.1016/j.trd.2015.09.011
1361-9209/

charging stations across the province (City of Surrey, 2012; JR, 2012). While the deployment of charging infrastructure has been moving forward in many cities, research on developing mathematical models for charging infrastructure siting is also growing. Xi et al. (2013) have formulated an optimization framework for charging station siting to maximize the amount of energy and the expected EVs recharged, by estimating charging demand as a function of household demographic variables (e.g. average total mileage driven) and macroeconomic variables (e.g. gasoline and electricity prices). Sathaye and Kelley (2013) estimate charging demand using a linear function of two terms—traffic and population—to minimize total distances between demand locations and charging stations. Sadeghi-Barzani et al. (2014) predict the charging demand based on the number of EV owners to minimize the total cost associated with charging which includes travel cost to stations and electricity cost. He et al. (2013) predict charging demand based on travel time, charging expenses, availability, and attractions to maximize total social welfare. Dong et al. (2014) use multiday travel data of 275 household in the Seattle metropolitan area to minimize the number of trips which cannot be completed using electricity. Despite the difference on scope and goals, these studies use non-exact algorithms to find local optimal solutions to our knowledge.

Two research gaps exist in the literature on siting public charging stations. First, methods currently used in estimating charging demand may not reflect the real world situation. Unlike refueling liquid fuels which only takes a few minutes to fill the tank, fully recharging the battery on an EV can take a much longer time, from 30 min to several hours depending on the charger power, battery size, and the state of charge of the battery (Dong et al., 2014). Therefore, EV charging is more likely to happen at the end of a trip instead of in the middle of a trip. In addition, EV owners can charge their vehicles at home during the night. As a result, using traffic flow volume or vehicle ownership density to estimate charging demand as predominately used in previous studies may not be valid. Secondly, few studies considered environmental impacts of EV charging as the objective function for global optimal solution. The ultimate goal of EV system deployment is to fulfill more travel needs using electricity instead of fossil-based liquid fuels. We aim to address both gaps in this study by (1) using large-scale real world vehicle travel data to better model charging demand and (2) maximizing electrified fleet vehicle-miles-traveled (VMT) as the objective function to find the global optimal solution. Our previous work has demonstrated that collective public parking "hotspots" extracted from real world vehicle trajectory data are good indicators of public charging demand (Cai et al., 2014). This research expands upon Cai et al. (2014) to develop an optimization model to solve for global optimization solutions for public charging station siting using large-scale real world vehicle travel data. In addition, the goal of our optimization model is to maximize electrified fleet VMT, which directly links to the environmental benefits of vehicle electrification.

Using Beijing, China as a case study, this paper presents an optimization framework which utilizes large-scale real world vehicle trajectory data for selecting the location of public charging stations to maximize electrified fleet VMT. The demonstrated optimization framework can be applied to other fleets in other cities using similar data. The case study also has its own policy relevance because Beijing plans to deploy 200,000 electric vehicles on road by 2017 and build 10,000 public charging stations (NAATBatt International, 2015; WantChinaTimes, 2013). Results from this study can help future decisions on developing public charging stations in Beijing. The proposed optimization model is implemented in GAMS with Cplex solver. In order to accommodate for the large-scale vehicle trajectory data in the model, we identify factors in model formulation, input data format, and settings of Cplex options that need to be adjusted to solve the model efficiently. In summary, major contributions of this paper include (1) formulating an optimization model which selects the location of public charging stations to maximize electrified fleet VMT; (2) incorporating vehicle travel patterns by using large-scale individual-based vehicle trajectory data to model public charging demand; (3) studying public charging infrastructure planning in Beijing as a case study; and (4) providing suggestions in model formulation and execution to handle large-scale data.

Mathematical formulation

EVs include battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). BEVs use electricity as the sole power source while PHEV has the flexibility of using both electricity and liquid fuels (Markel, 2010). In this paper we focus on PHEVs to allow drivers finishing trips on liquid fuels when batteries are depleted, because it is unclear how limited driving range of BEVs will affect the behavior of drivers.

Let $G(i,j,k)$ be a network with i candidate locations for installing public charging stations, j individual PHEVs, and k trips for each vehicle in the examined period. The time spent between two consecutive trips is defined as the dwell time.

Each vehicle (j) has a remained battery charge (R_{jk}) at the end of each trip (k) before starting its dwell time. For the convenience of modeling, R_{jk} is measured as the mileage that the vehicle can travel with the remaining electricity (battery range). R_{jk} can be formulated as shown in Eq. (1) (Dong et al., 2014). Negative values of R_{jk} represent the mileage that cannot be powered by electricity (i.e., powered by liquid fuels) in trip k. Eq. (2) shows the real remaining battery range ($\widehat{R}_{jk}$) of vehicle j at the end of trip k, which is forced to be non-negative.

$$R_{jk} = \widehat{R}_{jk-1} + E_{jk-1} - d_{jk} \quad \forall j \in J,\ \forall k \in K \tag{1}$$

$$\widehat{R}_{jk-1} = \max\{R_{jk-1}, 0\} \quad \forall j \in J,\ \forall k \in K \tag{2}$$

where R_{jk} is the remaining battery range of vehicle j at the end of trip k (mile), E_{jk-1} is the electricity recharged (measured in miles) for vehicle j during the dwell time between trip $k-1$ and trip k; and d_{jk} is the travel distance (miles) of vehicle j during trip k.