STATE OF CALIFORNIA • DEPARTMENT OF TRANSPORTATION

TECHNICAL REPORT DOCUMENTATION PAGE

TR0003 (REV 10/98)

1. REPORT NUMBER
CA16-2799

2. GOVERNMENT ASSOCIATION NUMBER

3. RECIPIENT'S CATALOG NUMBER

4. TITLE AND SUBTITLE
Strategic Charging Infrastructure Deployment for Electric Vehicles

5. REPORT DATE
May 2016

6. PERFORMING ORGANIZATION CODE

7. AUTHOR
Meng Li, Yinghao Jia, Zuojun Shen, Fang He

8. PERFORMING ORGANIZATION REPORT NO.
N/A

9. PERFORMING ORGANIZATION NAME AND ADDRESS
University of California, Berkeley
Civil and Environmental Engineering
Berkeley, CA 94720

10. WORK UNIT NUMBER

11. CONTRACT OR GRANT NUMBER
65A0529 TO 010

12. SPONSORING AGENCY AND ADDRESS
California Department of Transportation (Caltrans)
Division of Research, Innovation and System Information, MS-83
1227 O Street, Sacramento, CA 95814

13. TYPE OF REPORT AND PERIOD COVERED
Final Report, March 2015- May 2016

14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES

16. 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 a 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 insight 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 charge 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 fleets with similar dataset available, and the analysis results contribute to our understanding on electric vehicles' 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 80 km 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 the availability of chargers at stations to drivers can increase the electrification rate of VMT; and vi) the impact of stochasticity embedded in the trajectory data can be significantly mitigated by adopting the dataset covering a longer period.

17. KEY WORDS
trajectory dataset, plug-in hybrid electric vehicle, charging opportunity, electrification rate, public charging stations, vehicle miles traveled

18. DISTRIBUTION STATEMENT
No Restriction.

19. SECURITY CLASSIFICATION *(of this report)*
Unclassified

20. NUMBER OF PAGES
31

21. COST OF REPORT CHARGED

DISCLAIMER STATEMENT

University of California
Center for Economic
Competitiveness in
Transportation

Strategic Charging Infrastructure Deployment for Electric Vehicles

Final Report UCCONNECT 2016-TO010-65A0529

Max Shen; Chancellor's Professor; University of California, Berkeley
Meng Li; Associate Professor; University of California, Berkeley
Fang He; Ph.D; University of California, Berkeley
Yinghao Jia; Ph.D Candidate; University of California, Berkeley

Sponsored by

Caltrans

2016

Berkeley UC Irvine UCLA UCR UCSB CAL POLY POMONA

Strategic Charging Infrastructure Deployment for Electric Vehicles

Final Report

May 2016

Caltrans
CALIFORNIA DEPARTMENT OF TRANSPORTATION

Strategic Charging Infrastructure Deployment for Electric Vehicles

May 2016

Task 2799

Contract NO. 65A0529 TO 010

Principal Investigator: Dr. Zuo-Jun (Max) Shen

Department of Civil and Environmental Engineering

University of California, Berkeley

Berkeley, California 94720

Department of Industrial Engineering and Operations Research

University of California, Berkeley

Berkeley, California 94720

(510) 643-2392

maxshen@berkeley.edu

Table of Contents

Figures and Tables

ACKNOWLEDGEMENTS

The project is supported by UCCONNECT Research Grant.

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 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 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). As for Beijing, one of the biggest cities in China, there are about 36,000 electric vehicles being in use by the end of 2015, of which 23,500 were adopted in the year of 2015 alone. Among all the EVs, about 16,2000 vehicles are serving for public transportation such as transit and taxi; and the rest are used by private owners or companies.

However, there still exist several bottlenecks blocking the rapid development of EVs, such as the high cost of EV batteries, lack of charging infrastructure, and shortage of battery range. Moreover, it’s currently difficult for the EV market alone to conquer all of these obstacles. 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 adoption of EVs (He et al., 2015; Motavalli, 2010; GLOBLE-Net, 2012).

To assist policy makers with optimally deploying 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

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

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 b c, 2015; Jiang et al., 2012; Jiang and Xie, 2014). However, both above approaches make assumptions 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 patterns, 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 simulations to explore how to locate public charging stations among the existed 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 recognizing the important role Beijing is playing in the massive adoption of electric vehicles, this paper gathers the real-time vehicle trajectory data of 46,765 taxis in Beijing from October 1st to November 30th in 2014 and carries out a case study for Beijing. 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 taxi 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 plans. In order to improve the electrification rate of VMT and based on the simulation results, we further provide policy guidelines for 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. First, 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 available at stations. Therefore, our simulations are capable of accurately modeling the real-time operations of public charging station and reflecting the interactions of different PHEVs' charging behavior[2]. However, it is necessary for accurately estimating the electrification rate of VMT because recharging a PHEV battery is time-consuming and the times PHEV drivers choose for recharging has a large degree of overlap. Second, based on the proposed simulation framework, we further quantify the contribution of introducing the intelligent charging guidance system for improving the electrification rate of taxi VMT in Beijing. This analysis can offer insight for the development of a "smart charging" program that is devoted to applying the information technology to improving the utilization efficiency of public charging stations in the future. Third, 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 datasets 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 the basis of this dataset, we conduct time-series simulations to model PHEV drivers' operations and charging behavior, and then discuss how to locate public charging stations and guide charging behavior.

[2] Note that considering the impact of public charging stations' limited capacity will inevitably cause great computational challenges, especially for our case with 46,765 taxis.

2.1 Data Description and Preprocessing

To better characterize the heterogeneous travel patterns of individual taxi drivers, we examine the real-time vehicle trajectory data of 46,765 taxis in Beijing from October 1st to November 30th in 2014, collected by smartphones and on-board devices.[3] The dataset includes 3.37 billion data points, which track each taxi's location (longitude and latitude) and speed (km/hour) every 30 seconds. Table 1 shows one sample of the records in the dataset. To clean up the raw data, we remove the points that are duplicated and incorrect.

Table 1. Record Sample

ID	Time stamp	Speed (km/hour)	Longitude	Latitude
84471	201411120715	32	116.8198	40.34311

Figure 1 depicts the GPS trajectory of a randomly selected taxi in blue lines from October 1st to November 30th in 2014, which covers most parts of the roads in Beijing.

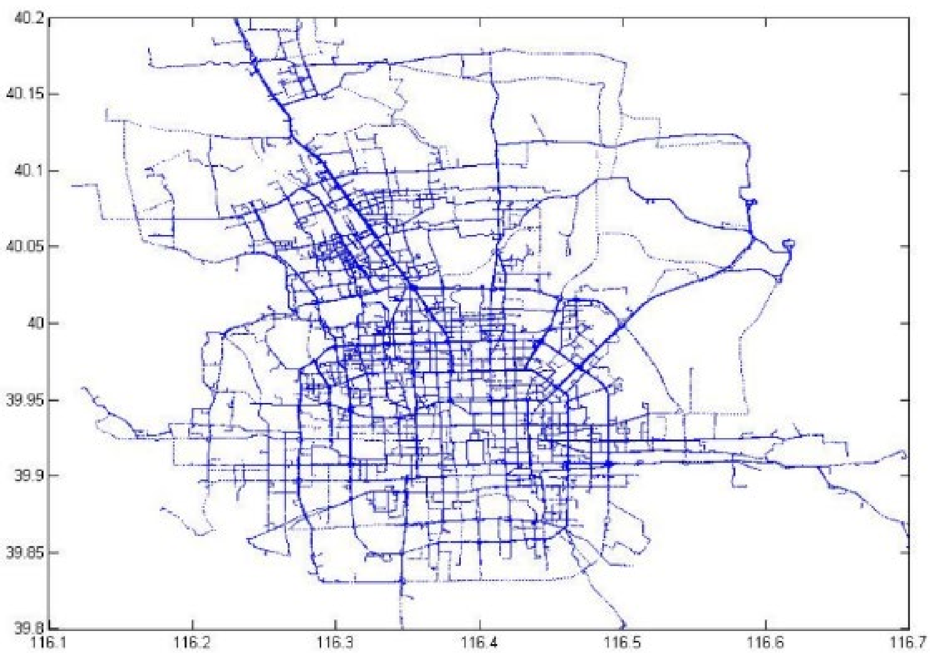


Figure 1. GPS trajectory sample

[3] The total number of taxis in Beijing is approximately 66,000 (Huo et al., 2012; Zheng et al., 2011).

In this research, we focus on PHEVs, which are still capable of driving by consuming gasoline fuel after the battery is out of charge. It is hence assumed that the travel behavior of taxi drivers remains unchanged after adopting PHEVs. Note that this assumption is also adopted by many previous studies (e.g. Dong et al., 2014; Cai et al., 2014). In addition, considering the dataset will be iteratively utilized in the following simulation, we thus develop an approach to compress it. Generally, recharging EVs is much more time-consuming than refueling a conventional gasoline vehicle. For instance, 20 hours are needed to fully recharge a 24 kWh battery at the power level of 1.2 kW, whereas a charger with 60 kW power level still needs 24 minutes (He et al., 2014; ETEC, 2010). Therefore, we assume that a PHEV will not recharge if the dwelling time at an intermediate stop is less than 30 minutes. Based on this criterion, the trajectory of a vehicle could be divided into several trips. Specifically, we first order each vehicle's trajectory data points by time. Next, for each vehicle, we cut the trajectory into separate trips at the points corresponding to parking where the duration is more than 30 minutes. For each trip, we only record the time stamps and locations of its origin and destination, as well as the calculated trip distance, and all the resting data points are deleted. As a result, the data size is significantly reduced, which greatly speeds up the simulations described in the next section.

2.2 Definition of Charging Opportunities

Given the public charging station deployment plan, we focus on conducting time-series simulations to estimate the electrification rate of VMT for PHEV taxis. First of all, we define the PHEV charging opportunity from the aspects of time window, charging demand and charger availability. In the simulation model, a PHEV will recharge its battery if and only if all the following three conditions are met:

i. The PHEV is in a charging time window and its duration is no less than 30 minutes. Note that we define charging time window as the time slot after a trip ends and before the consecutive trip starts.
ii. The state of charge (SOC) of PHEV's battery is below a predefined threshold.
iii. There are available chargers in the public charging station.

The above second condition implies that analyzing charging behavior of a PHEV needs to track its SOC. Namely, the amount of electricity a PHEV charges affects when and where its next charging demand occurs, leading to the fact that we could not study each charging behavior separately but needed to conduct a time-series simulation to analyze its trip chain. Furthermore, from the above third condition, it is possible that one charger's occupation by one vehicle eliminates another vehicle's charging opportunity. In other words, the third condition reveals that the charging behaviors of different vehicles are correlated and hence we cannot analyze each vehicle separately. To summarize, the above analyses suggest modeling charging and operations of a PHEV taxi fleet needs a time-series simulation model that takes into account all the vehicles simultaneously. However, the big dataset (46,765 taxis for two months) inevitably creates a computational burden and challenge for conducting this time-series simulation. In the following section, we will describe the simulation model, as well as how to solve it efficiently.

2.3 Time-series Simulation Model

Assume the extracted trip-chain information from the dataset sufficiently represents the travel patterns of PHEV drivers. We simulate their traveling and charging behaviors in this section. After the simulation, the electrification rate of VMT can be thereby estimated. Figure 2 shows the flow chart of the simulation model. Once again, we emphasize that the time-series simulation model requires that drivers follow the existing trip-chain profile and will consider recharging only when the three conditions defined in Section 2.2 are satisfied. In the simulation, time is discretized, and as the time step propagates, each PHEV's SOC is updated accordingly. The update is implemented through utilizing three tables, i.e., time window chart, station operation chart, and vehicle driving profile. When a PHEV's SOC falls below the pre-determined threshold, we check if there is a charging time window and also search the nearby charging station to verify the availability of chargers. If all these conditions are satisfied, the vehicle will be recharged and the above three tables are updated correspondingly.

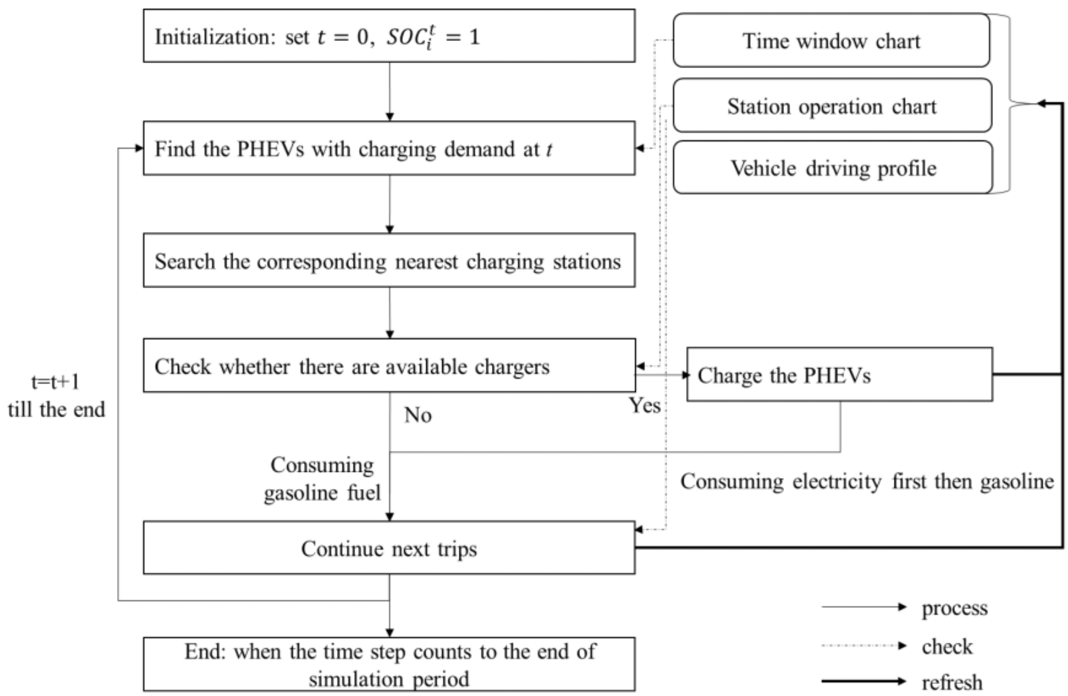


Figure 2. Simulation model flow chart

The details of the simulation model are shown as follows:

Step 1: Set $t = 0,\ SOC^{(} = 1,\ \forall i$. Choose the time step as five minutes.

Step 2: Set the threshold SOC as 0.2. At time index t, find the PHEVs with charging demand, i.e., SOC below 0.2.

Step 3: For any PHEV with charging demand, identify its nearest charging station, which implies drivers tend to choose the nearest station for recharging.[4] Due to the fact that the roads in Beijing are typically vertical and horizontal, we calculate the Manhattan distance between a PHEV and a charging station.

Step 4: Send the PHEV to the identified station. If there is at least one charger available within five minutes of arrival, recharge the vehicle. The recharging time equals the minimum time needed to replenish the battery and the remaining time of the charging time window.

4 It is assumed that without the information of nearby charging stations' utilization, drivers will choose the nearest stations to seek for charging opportunities. In Section 2.4, we will discuss an intelligent charging guidance system, devoted to assisting drivers to better choose stations.

Otherwise, the PHEV will continue its trip, consuming electricity first and then utilizing the gasoline after the electricity is exhausted.

Step 5: Set $t = t + 1$. If t is the end of the simulation period, end the simulation. Otherwise, go to Step 2.

In the above simulation procedure, the most time-consuming part is finding all PHEVs with charging demands. The naïve way of doing this is to check the SOC of each PHEV at each time step, which leads to roughly 260 million checks of PHEV SOC in our dataset and greatly increases the time of running the simulation model. Here, we introduce a more efficient method, which we refer to as the Tetris method. Specifically, we first construct the time window chart whose rows and columns respectively correspond to time steps and vehicle IDs, as shown in Figure 3. While running the simulation model, we use this chart to assist us with efficiently identifying the charging demands of PHEVs by following the procedure below:

i. We initiate the values of all the elements in this table at zero.

ii. Taxi drivers do not charge their vehicles during traveling. So, we replace zero by -1 in the elements whose corresponding vehicles are traveling and their SOC is above the predefined threshold.

iii. During the simulation, if a vehicle chooses to charge in a station, we replace zero by the station number in the elements that correspond to the entire charging period. Recall that the vehicle's charging time equals the minimum of needed charging time and available charging time.

iv. After finishing charging, the PHEV continues to travel. Let i denote the trip immediately after finishing charging. Based on the vehicle driving profile, we can easily find the trip j, at which the SOC of the PHEV begins to drop below the threshold again. Replace zero by -1 in the elements between trips i and t.

v. For vehicle k, let C_k represent the number of row where zero first appears in the elements. Find the vehicle with the smallest C_k and conduct the charging opportunity check for it. Run steps ii-v iteratively.

Figure 3 further illustrates Steps iv and v of the Tetris method.

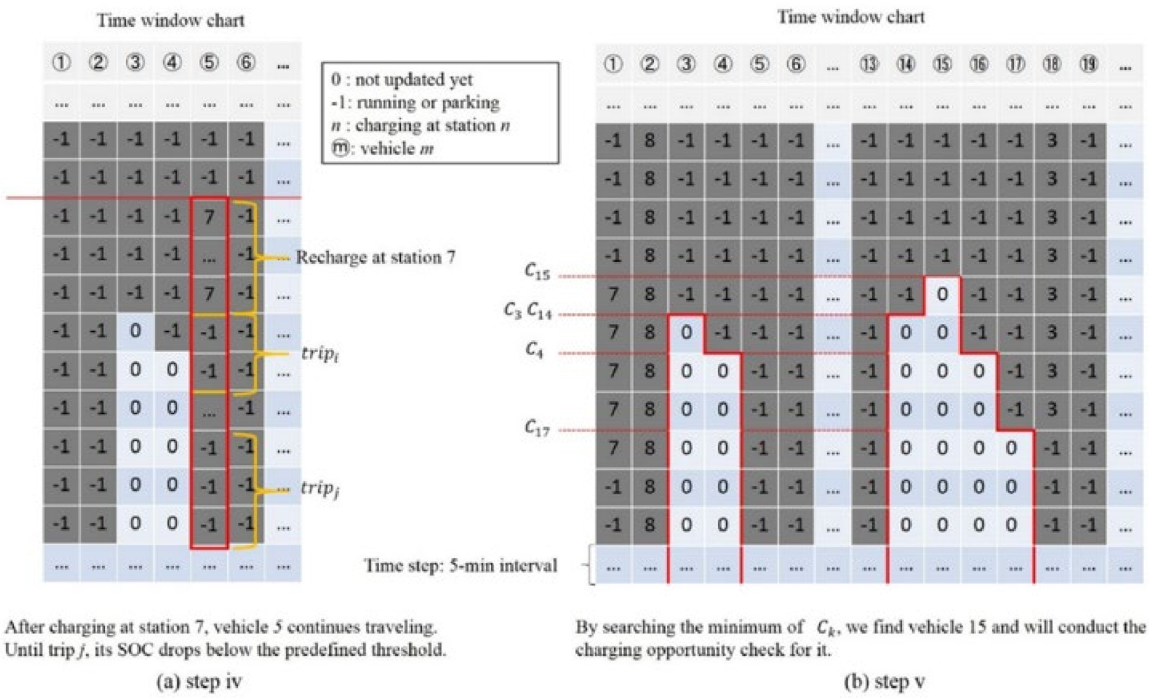


Figure 3. Tetris method

2.4 Public Charging Station Location and Intelligent Charging Guidance System

Public charging stations should be located to best satisfy the recharging needs of PHEVs. We cluster the locations of charging time windows of PHEVs and then locate charging station to each cluster. For instance, if we plan to locate 50 public charging stations, we will apply the K-means method to partition the locations of charging time windows into 50 clusters and then locate a station at the centroid of each cluster.[5] Note that this locating method is consistent with the suggestion by Cai et al. (2014), that the number of parking events serves as a good criterion to locate stations. Figure 4 shows the location plans corresponding to 50, 100, 300 and 500 stations, in which each dot represents a charging time window belonging to a PHEV. To further explore the location plan, we locate these stations in the electronic map of Beijing and observe whether these locations suit the clusters and parking lots of Beijing well, indicating the clusters of charging time windows indeed reveal the possible future charging needs.

[5] We do not require the station locations to sit in the existed gasoline stations in consideration of the fact that the existed gasoline stations do not necessarily have enough space to accommodate many PHEVs that simultaneously recharge their batteries.

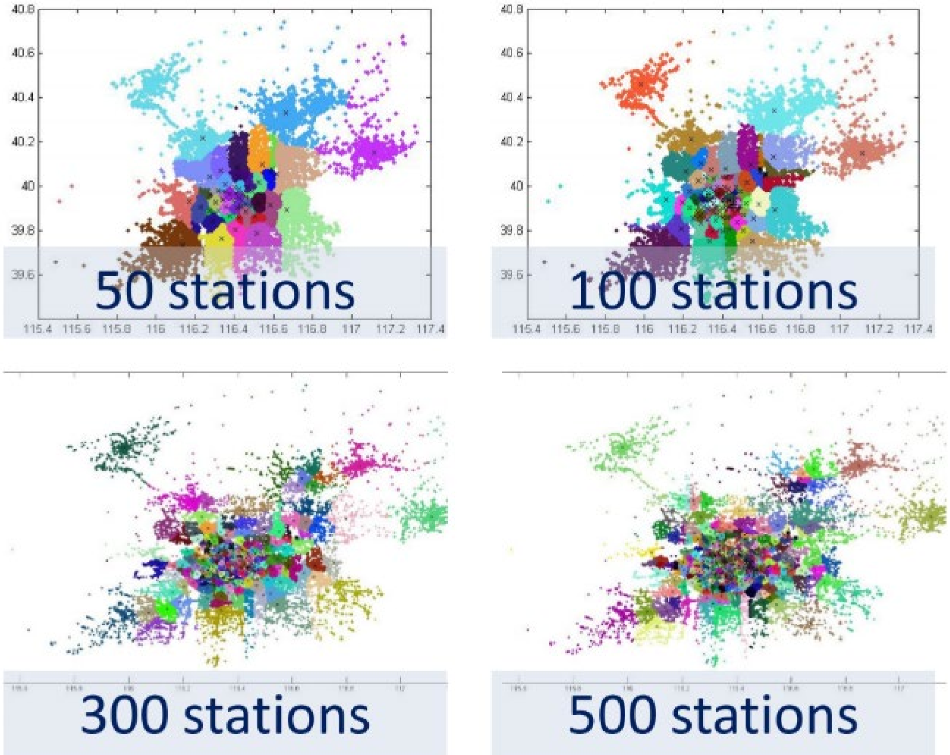


Figure 4. Location plan of public charging stations

Recall that in the proposed simulation model, PHEVs with charging demands always choose the nearest stations to seek for charging opportunities in spite of the utilization levels of the stations, specifically if PHEV drivers have no access to the real time charging information. Hereinafter, we refer to it as the nearest-station strategy. However, with the development of information and smartphone technology, an intelligent charging guidance system is becoming possible (Charge Point, 2016). In essence, the intelligent charging guidance system can not only feed the charger availability information to drivers but also provide guidance for their charging station choices. In this paper, besides the above nearest-station strategy, we also consider the possible adoption of the intelligent charging guidance system. Through a smartphone application or on-board equipment, drivers can conveniently connect to the intelligent charging guidance system to check the utilization levels of all charging stations. The system will also navigate a vehicle to the station that currently has the most available chargers within a pre-defined distance to the vehicle. In Section 3, we will quantify the effects of introducing such a system.

2.5 Simulation Environment

To provide guidelines for the charging station deployment planning, we run the simulation model, varying the number of charging stations, the number and types of chargers for each station, and battery ranges. Table 2 lists the values or ranges of the parameters in the simulations (Morrow et al., 2008; Dong et al., 2014):

Table 2. Parameter values

Parameter	Value
Fast charger power	60kW
Slow charger power	6kW
Number of charging stations	50-500
Number of fast chargers at each station	0-4
Number of slow chargers at each station	10-60
Battery range	10-80km
SOC threshold	0.2
Driving efficiency	0.2kWh/km

3. RESULTS

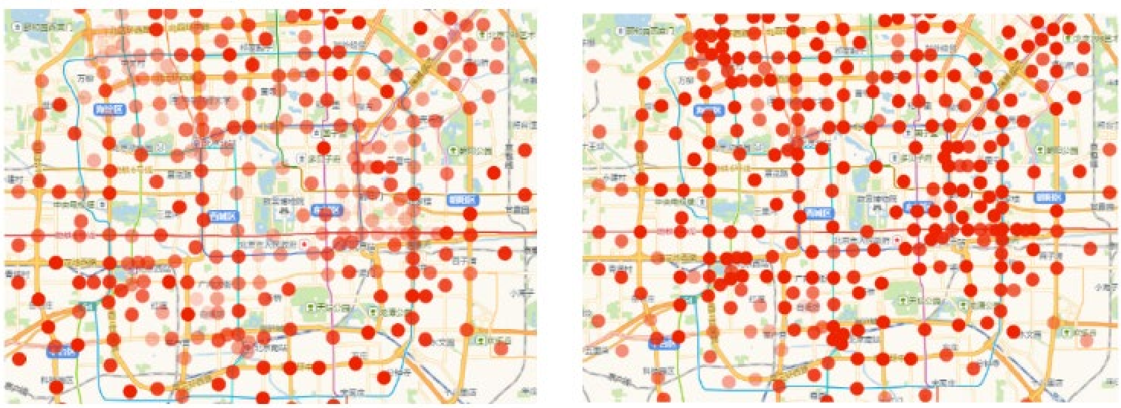
In this section, we first show the simulation results of the base scenario, i.e., 500 stations, 30 slow chargers (each with the charging power of 6 kW) at each station, no intelligent charging guidance system, battery with the range of 80 km, and home charging available.[6] Then, we conduct the sensitivity analyses with respect to the number of chargers per station, charger types, and the availability of home charging and intelligent charging guidance system.

3.1 Simulation Results of Base Scenario

We apply the K-means clustering method to locating the public charging stations. From the simulation results, the electrification rate of VMT reaches 54.3%, equivalent to electrifying 170 million vehicle miles. We also run the simulation with the 500 public charging stations uniformly deployed, and the electrification rate of VMT is only 42.6%, which further justifies the proposed approach of locating public charging stations to the clusters of PHEVs' charging time windows.

[6] Consistent with Cai and Xu (2013), home charging occurs when the duration of charging time window exceeds eight hours.

Figure 5 illustrates the average number of chargers utilized at midnight and noon respectively during these two months. Each red circle represents a charging station, and its shade corresponds to the average number of occupied chargers (the depth of the color increases with the number of occupied chargers). It can be observed that more public chargers, especially in business areas, are occupied at noon than midnight, which could be explained by the fact that many taxis do not operate during night and hence prefer home charging or the public charging stations in suburban areas.



Midnight Noon

Figure 5. The average number of utilized chargers

Figure 6 illustrates the daily average aggregate charging power in public charging stations in November. Consistent with Figure 5, the charging power reaches the daily peak at around 13:00. After midnight, there also exists a peak time, implying public charging stations are also utilized at night (mostly in suburban areas as demonstrated in Figure 5).

Figure 7 depicts the distribution of average daily utilization levels among public charging stations. For each station, the daily utilization level is defined as the ratio of the total amount of energy PHEVs recharge at it over the amount of energy it can provide in one day (calculated as the total power of chargers multiplied by 24 hours). From Figure 7, the median utilization level is 0.15, demonstrating the public charging station's daily utilization level is not high in general. This could be possibly explained by the temporal and spatial imbalance of PHEV drivers' recharging behavior, revealed in Figures 5 and 6.

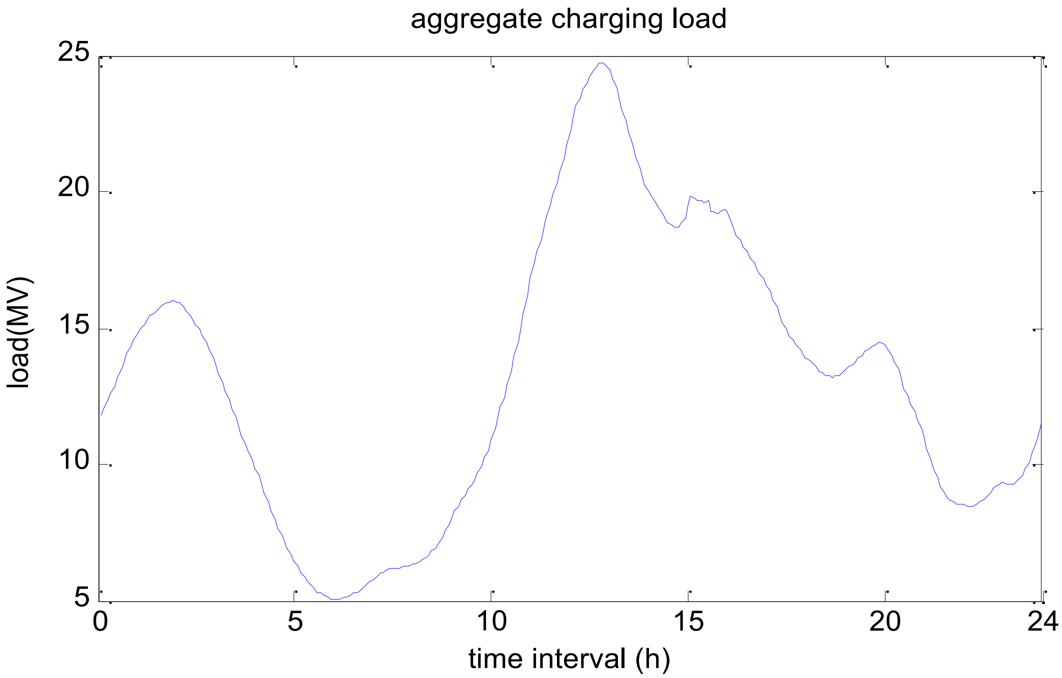


Figure 6. Daily aggregate average charging power

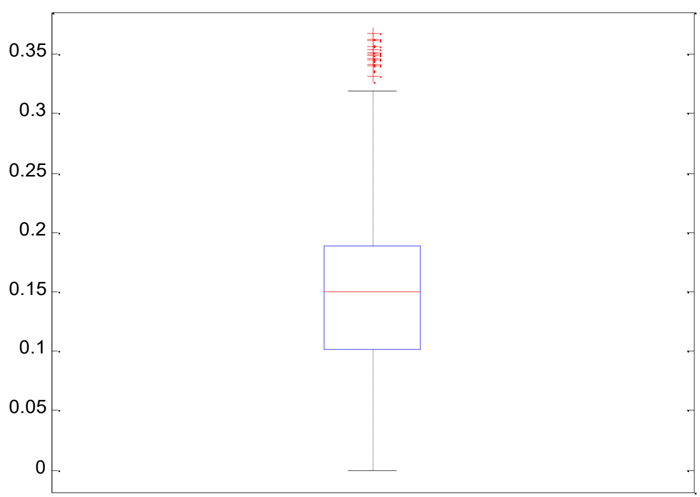


Figure 7. Distribution of average daily utilization levels for public charging stations

3.2 Sensitivity Analyses

3.2.1. Home-charging

We first evaluate the impact of the availability of home charging on the electrification rate of VMT. We define the electrification gap as the difference between the electrification rates of VMT with and without home charging. Figure 8 compares the electrification gaps under the combination of different battery ranges and charging infrastructure plans, among which the poor, normal and good charging infrastructure plans all correspond to locating 500 stations. However, the numbers of slow chargers at each station are 10, 20 and 30 for the poor, normal and good charging infrastructure plans, respectively. It can be observed that when the battery range is below 20 km, the values of the electrification gaps for all the three plans are below 0.06, but the values of electrification gaps increase with the battery range. The values of the electrification gaps under the poor charging infrastructure plan are the highest among the three plans. From these observations, we can conclude that: the effect of promoting home charging is limited when the battery range of PHEVs is not large enough; in the early stage of EV development when the public charging infrastructure is not sufficient, promoting home charging is a relatively promising way to improve the electrification rate of VMT.

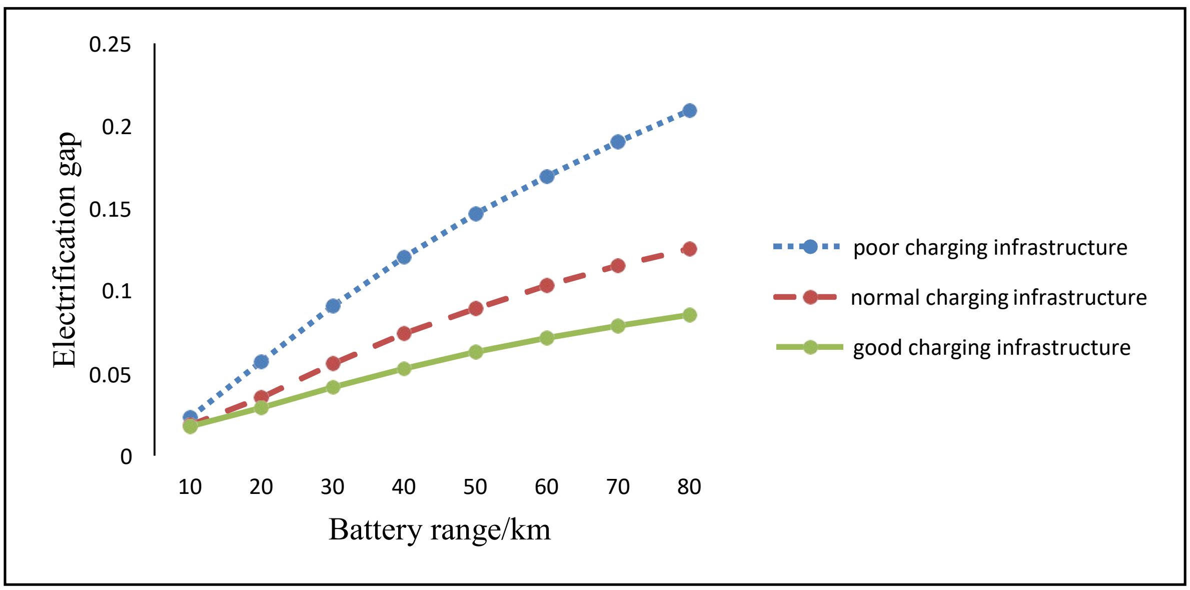


Figure 8. The influence of charging infrastructure's quality

3.2.2 Charger types

As demonstrated in Table 2, a fast charger is ten times as efficient as a slow charger. However, its deployment cost and requirement on the electricity circuit are also higher. If deploying fast chargers in stations is possible, we explore how to determine the specific numbers of both types. Fixing the total number of stations at 500 and setting the total charging power at each station to 180 KW (the same as base scenario), Figure 9 compares the electrification rates of VMT for four different charger plans under different battery ranges. The four plans respectively deploy 30 slow chargers, 2 fast and 10 slow chargers, 1 fast and 20 slow chargers, and three fast chargers, at each located charging station. We observe some interesting results: i) when the battery range is less than 30 km, the difference among different plans is not obvious; ii) as the battery range continues to grow, the electrification rate of VMT corresponding to the plan of 2 fast and 10 slow chargers is the highest, followed by 1 fast and 20 slow chargers and then 30 slow chargers. This is because the recharging time of most PHEVs is limited and fast chargers can further extend their electric miles. Furthermore, the plan of three fast chargers performs the worst among the four plans. This could be caused by the fact that the number of chargers is not sufficient enough to simultaneously accommodate several PHEVs' recharging when their arrival time at the station is close, which often happens in business areas. We note that this observation corresponds to the scenario where PHEV drivers are only willing to wait at most five minutes at stations if there are no chargers available. [7] To summarize, without changing the total power of a public charging station, introducing the appropriate number of fast chargers will contribute to the electrification rate of VMT, but replacing all slow chargers with fast chargers may not necessarily increase the electrification rate of VMT.

[7] We assume PHEV drivers will not wait a long time at charging stations for available chargers in consideration of the following aspects. First, PHEVs are still capable of operating even after their electricity is exhausted, hence, recharging their batteries is not mandatory for completing following trips. Second, besides recharging, PHEV drivers may plan to conduct some other activities such as eating and resting during the time window. If so, it may not be desirable for them to spend all the dwelling time waiting at public charging stations.

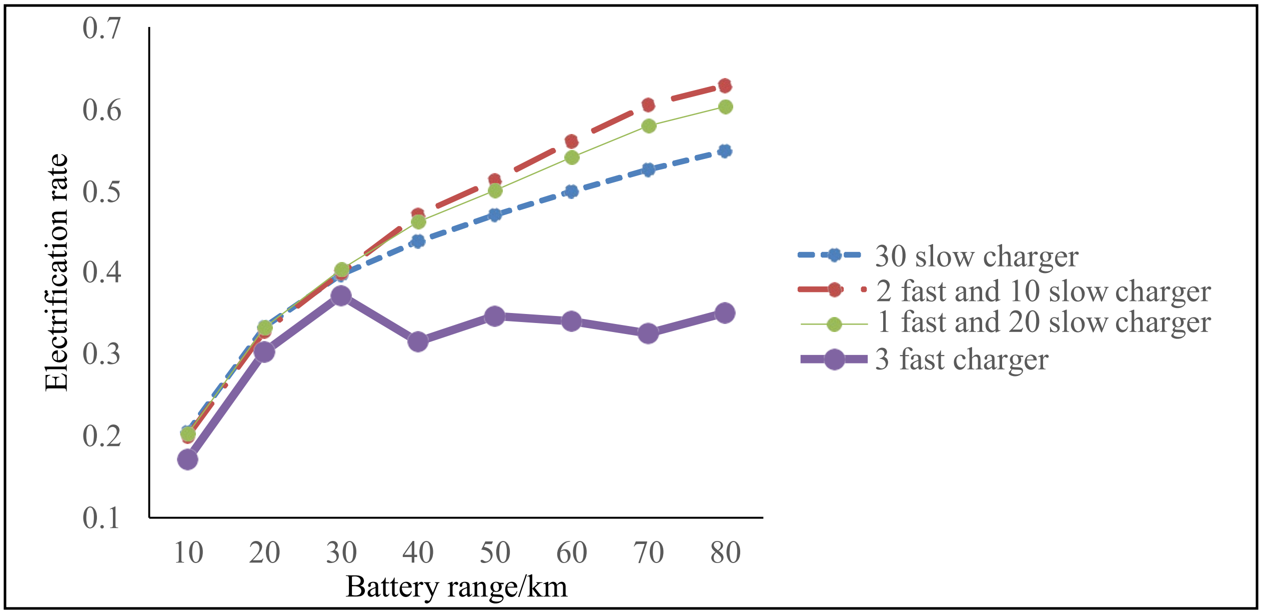


Figure 9. Impacts of charger types

3.2.3 The station scale

With regard to the station scale, there are generally two trends: One is to construct huge stations with many chargers at each station and the other is to build more small stations with fewer chargers. Without the sensitivity analyses, it's difficult to determine the scale of stations to best satisfy the charging needs.

Fixing the total charging power, we vary the number of stations from 50 to 1000. Inspired by Figure 9, we mix fast and slow chargers at each station. Table 3 shows the number of charger types under different station numbers. Figure 10 compares the electrification rates of VMT for different charging station numbers under different battery ranges. In spite of the battery range, as the station number increases and the station scale decreases, the electrification rate firstly increases and then remains nearly unchanged, which intuitively makes sense because the charging stations need to be spread out sufficiently to spatially satisfy the fleet charging demands. Moreover, if economies of scale exist in charging station deployment, 500 public charging stations will best fit our case as the marginal increase of the electrification rate is relatively small after 500.

Table 3. Numbers and types of chargers

Station Number	Number of slow chargers at each station	Number of fast chargers at each station
50	100	20
100	50	10
300	20	3
500	10	2
600	15	1
750	10	1
900	7	1
1000	5	1

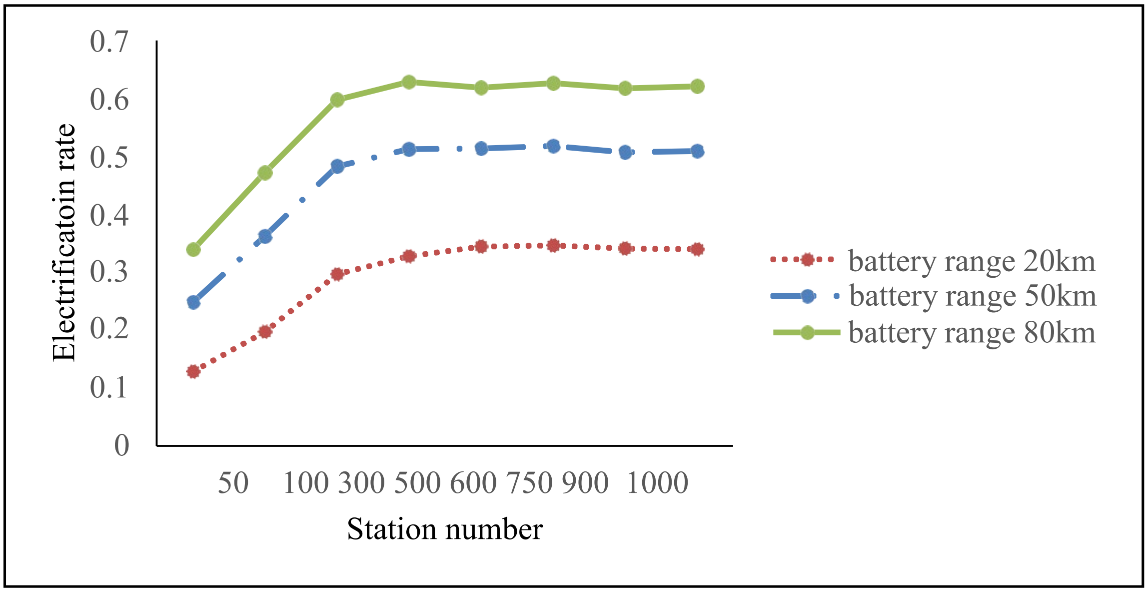


Figure 10. Impacts of station scales

3.2.4 Intelligent charging guidance system

Recall that we mentioned the possible adoption of an intelligent guidance system. In particular, the system is capable of feeding the information of charger availability at each station to PHEV drivers and navigating them to the stations with the most available chargers within a pre-defined distance to the vehicle. Figure 11 compares the electrification rate gaps between the nearest-station strategy and intelligent charging under different battery ranges. As expected, adopting the intelligent charging guidance system can increase the electrification rate of VMT by around 0.027 as it improves the possibility for PHEV drivers to find available chargers. Moreover, we also observe that the increase rate is not sensitive to battery range.

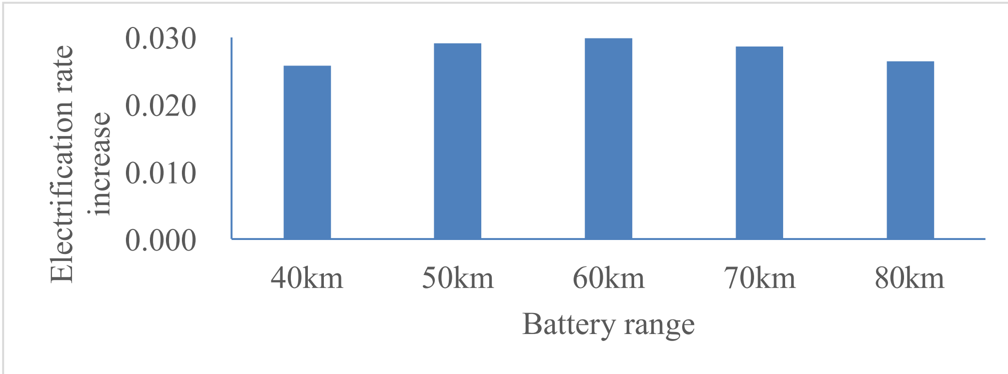


Figure 11. Impacts of intelligent charging guidance system

3.2.5 Contours of electrification rate of VMT

To explore the relation among the electrification rate of VMT, battery range, and the total number of public chargers, we fix the total number of public charging stations as 500 and depict the contours of electrification rate of VMT in Figure 12 by varying the number of slow chargers at each station from zero to 30, and battery range from 10 km to 80 km. If denoting G, E and N as the electrification rate, battery range, and the number of slow chargers respectively, we can observe that $\frac{67}{68} > 0$, $\frac{67}{6:} > 0$, $\frac{67;}{6;8} < 0$, $\frac{67;}{6;:} < 0$. It reveals that the electrification rate increases with the battery range or the total number of chargers, and the rate of returns on increasing battery range or the number of chargers diminishes as these two factors (E and N) increase. Moreover, we also see $\frac{67;}{686:} > 0$, which could be explained because these two factors support each other, i.e., one factor will perform better when the other is at a high level. Lastly, based on the map of contours, we can identify all the possible combinations of E and N to achieve a target electrification rate. This could potentially support the decision-making process when a taxi fleet company electrifies its vehicles.

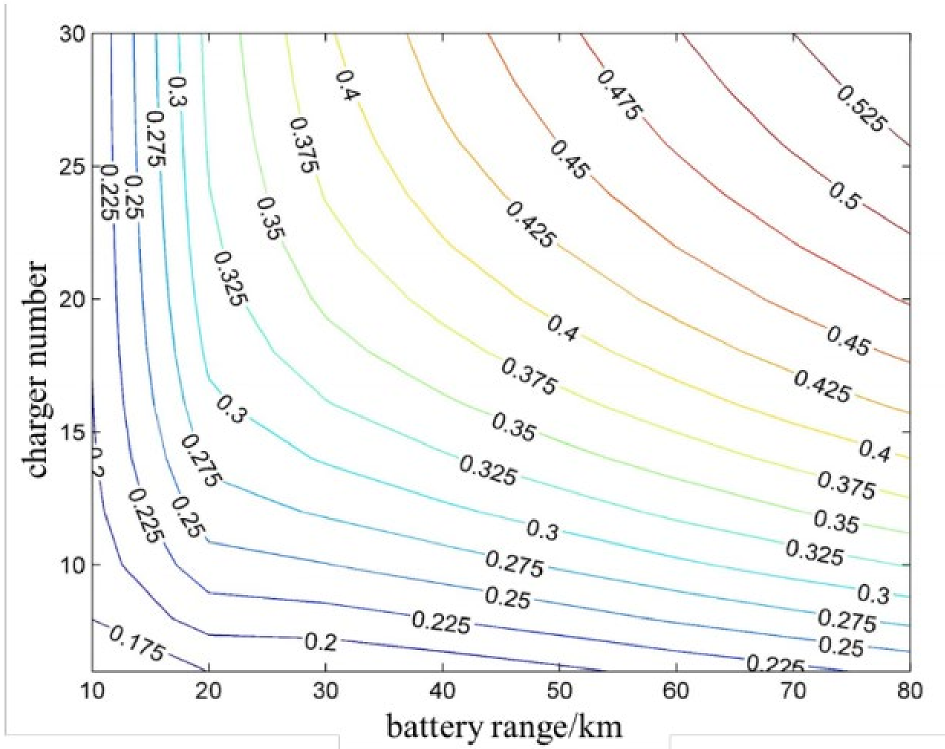


Figure 12. Contours of electrification rate of VMT

3.2.6 Dataset validation

The proposed simulation model is based on the trajectory data of a taxi fleet. In practice, taxis' trajectories vary from day to day. To explore the impact of the stochasticity embedded in the taxi trajectory data on the electrification rate of VMT, we respectively divide the dataset into eight, four and two components. Each of the eight, four and two components correspond to one week, one half month, and one month of the two months, respectively. Then, the simulation is run independently for each component to estimate the electrification rate of VMT. Figure 13 compares the standard deviation of the estimated electrification rates. For instance, if we divide the dataset into eight components (each one corresponds to one week), the standard deviation of eight estimated electrification rates are 0.0271, 0.0273 and 0.0263 under the battery ranges of 40km, 60km and 80km, respectively. It can be observed that as the length of the dataset's corresponding period increases, the standard deviation of the estimated electrification rates decreases. For the one-month-long dataset, the standard deviation is as small as 0.0158, implying that the impact of stochasticity from the trajectory data could be substantially mitigated by adopting the dataset covering a longer period.

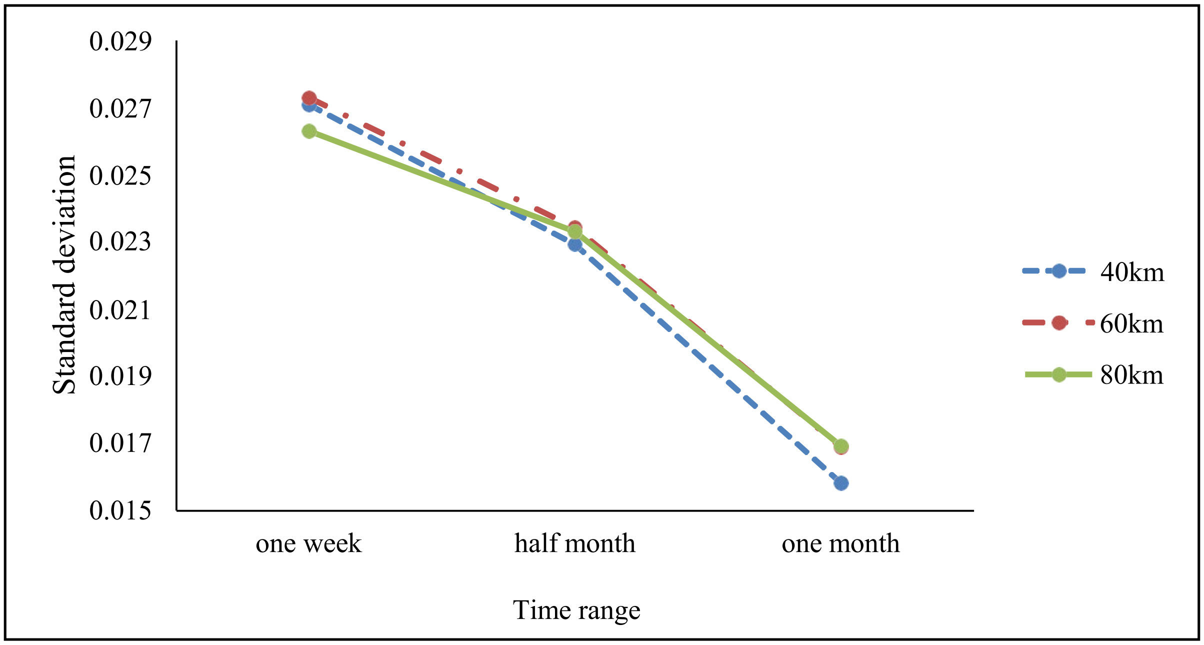


Figure 13. Impacts of the length of dataset's corresponding period

4. CONCLUSION

Using the two-month trajectory dataset of 46,765 taxis in Beijing, this study proposes a time-series simulation model to accurately quantify the electrification rate of VMT by taxi fleet, which considers not only the capacity of public charging stations but also the possible adoption of intelligent charging guidance system. We further cluster the charging time windows of PHEVs to locate public charging stations. Based on the proposed simulation model, we lastly estimate the impacts of charger type, charging station scale, home charging, and intelligent charging guidance system on the electrification rate of VMT by taxis in Beijing. Main findings are summarized as follows.

- For the base scenario of 500 public stations, 30 slow chargers at each station, no intelligent charging guidance system, battery with the range of 80 km, and home charging available, the electrification rate of VMT reaches 54.3%, equivalent to electrifying 170 million vehicle miles in Beijing.
- When the public charging infrastructure is not sufficient, facilitating home charging is a promising way to increase the electrification rate of VMT especially for the high range PHEVs.
- Without changing the total power of charging stations, introducing an appropriate number of

fast chargers will contribute to the electrification rate of VMT, but replacing all slow chargers with fast chargers may not necessarily increase the electrification rate of VMT.

- Breaking the charging stations into smaller ones and spatially distributing them will increase the electrification rate of VMT, but its marginal effect becomes relatively small after the number of stations exceeds 500.
- Adopting an intelligent charging guidance system can increase the electrification rate of VMT by around 0.027.
- The impact of stochasticity embedded in the trajectory data could be substantially mitigated by adopting the dataset covering a longer period.

This study assumes the PHEV's SOC decreases linearly with the traveled distance. We will further extend the simulation framework by adopting more sophisticated models to track SOC of PHEVs (e.g., Yang et al., 2015). Another future study is to investigate how to design the intelligent charging guidance system to improve the electrification rate of VMT. For instance, besides navigating PHEVs to currently available chargers, we could explore adding additional features into the guidance system such as making reservations for charging, and predicting the utilization levels of charging stations in the future.

REFERENCES

Andrews, M. et al., 2012. Modeling and optimization for electric vehicle charging. Available at: http://ect.bell-labs.com/who/gtucci/publications/ev_conf.pdf.

Berman, O., Larson, R. C., & Fouska, N. 1992. Optimal location of discretionary service facilities. Transportation Science, 26(3), 201-211.

Berman, O., Hodgson, M., Krass, D., 1995. Flow intercepting models. In: Z. Drezner, ed. Facility Location: A Survey of Applications and Methods. New York: Springer, pp. 389-426.

Cai, H. and Xu, M., 2013. Greenhouse gas implications of fleet electrification based on big data-informed individual travel patterns. Environmental science & technology, 47(16), pp.9035-9043.

Cai, H., Jia, X., Chiu, A. S., Hu, X., & Xu, M. 2014. Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. Transportation Research Part D: Transport and Environment, 33, 39-46.

Charge Point, 2016. < https://na.chargepoint.com/charge_point> (accessed February 24, 2016).

China State Council, 2012. Notice of the State Council on Issuing the Planning for the Development of the Energy-Saving and New Energy Automobile Industry (2012-2020). http://www.gov.cn/zwgk/2012-07/09/content_2179032.htm (accessed February 20, 2016)

Dong, J., & Lin, Z. 2012. Within-day recharge of plug-in hybrid electric vehicles: energy impact of public charging infrastructure. Transportation Research Part D: Transport and Environment, 17(5), 405-412.

Dong, J., Liu, C., Lin, Z., 2013. Charging infrastructure planning for promoting battery electric vehicles: an activity-based approach using multiday travel data. Transportation Research Part C 38, pp. 44-55.

ETEC 2010. "Electric Vehicle Charging Infrastructure Deployment Guidelines for the Oregon I-5 Metro Areas of Portland, Salem, Corvallis and Eugene." http://www.oregon.gov/odot/hwy/oipp/docs/evdeployguidelines3-1.pdf (accessed February 20, 2016).

GLOBLE-Net,2012. http://www.globe-net.com/articles/2012/april/9/bc-plan-for-electric-car-charging-stations-may-unleash-vehicles-around-province/ (accessed February 20, 2016).

He, F., Wu, D., Yin, Y., Guan, Y., 2013a. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. Transportation Research Part B 47 (1), 87-101.

He, F., Yin, Y. and Zhou, J., 2013b. Integrated pricing of roads and electricity enabled by wireless power transfer. Transportation Research Part C: Emerging Technologies, 34, pp.1-15.

He F, Yin Y, Wang J, Yang Y, 2013c. Sustainability SI: optimal prices of electricity at public charging stations for plug-in electric vehicles. Netw Spat Econ. doi:10.1007/s11067-013-9212-8.

He, F., Yin, Y., Lawphongpanich, S., 2014. Network equilibrium models with battery electric vehicles. Transportation Research Part B 67, 306-319.

He, F., Yin, Y., Zhou, J., 2015. Deploying public charging stations for electric vehicles on urban road networks. Transportation Research Part C 60, 227-240.

He, F., 2014. Optimal Deployment and Operations of Public Charging Infrastructure for Plug-in Electric Vehicles (Doctoral Dissertation). University of Florida, Gainesville.

Hodgson, M. J., 1990. A Flow-capturing location−allocation model. Geographical Analysis, 22(3), 270-279.

Hodgson, M., Berman, O., 1997. A billboard location model. Geographical and Environmental Modeling 1, pp. 25-45.
Huo, H. et al, 2012. Vehicle-use intensity in China: current status and future trend. Eng. Policy 43, 6–16.
Jiang, N., Xie, C. and Waller, S., 2012. Path-constrained traffic assignment: model and algorithm. Transportation Research Record: Journal of the Transportation Research Board, (2283), pp.25-33.
Jiang, N. and Xie, C., 2014. Computing and analyzing mixed equilibrium network flows with gasoline and electric vehicles. Computer‐aided Civil and Infrastructure Engineering, 29(8), pp.626-641.
Karplus, V.J., Paltsev, S. and Reilly, J.M., 2010. Prospects for plug-in hybrid electric vehicles in the United States and Japan: A general equilibrium analysis. Transportation Research Part A: Policy and Practice, 44(8), pp.620-641.
Krupa, J.S., Rizzo, D.M., Eppstein, M.J., Lanute, D.B., Gaalema, D.E., Lakkaraju, K. and Warrender, C.E., 2014. Analysis of a consumer survey on plug-in hybrid electric vehicles. Transportation Research Part A: Policy and Practice, 64, pp.14-31.
Motavalli, 2010. "Toyota and Tesla Plan an Electric RAV4". New York Times.
Querini, F. and Benetto, E., 2014. Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine. Transportation Research Part A: Policy and Practice, 70, pp.149-161.
Shukla, A., Pekny, J., Venkatasubramanian, V., 2011. An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles. Computers and Chemical Engineering 35, pp. 1431-1438.
US Department of Energy, 2013. http://www.fueleconomy.gov/feg/evsbs.shtml (accessed March 24, 2015).
XinhuaNet, 2014. http://news.xinhuanet.com/tech/2014-06/30/c_126689597.htm (accessed March 8, 2016).
Yang, Y., Yao, E., Yang, Z. and Zhang, R., 2015. Modeling the charging and route choice behavior of BEV drivers. Transportation Research Part C: Emerging Technologies(in press).
Zheng, Y. et al., 2011. Urban computing with taxicabs. In: Proceedings of the 13th International Conference on Ubiquitous Computing. ACM, Beijing, China, pp. 89–98.