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

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A B S T R A C T

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

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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).

the basis of this dataset, we conduct time-series simulations to model PHEVs' operations and charging behavior, and then discuss how to locate public charging stations and guide charging behavior.

2.1. Data Description and preprocessing

To better characterize the heterogeneous travel patterns of individual taxis, we examine the real-time vehicle trajectory data of 46,765 taxis in Beijing from October 1 to November 30 in 2014, collected by smartphone and on-board device.[2] The dataset includes 3.37 billion data points, which track each taxi's location (longitude and latitude) and speed every 30s. 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.

Fig. 1 depicts the GPS trajectory of a randomly selected taxi in blue[3] lines, which covers most parts of the roads in Beijing.

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.[4] Note that this assumption is also adopted by many previous studies (e.g. Dong et al., 2013; 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, it needs 20h to fully recharge a 24kWh battery at the power level of 1.2kW. A charger with 60kW power level still needs 24min (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 30min. 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 the parking whose duration is more than 30min. 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 rest 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 30min. 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 PHEV needs to track its SOC. Namely, the amount of electricity 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 need 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 that modeling charging and operations of 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 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 that the extracted trip-chain information from the dataset represents the travel patterns of PHEV drivers well. We simulate their traveling and charging behaviors in this section. After the simulation, the electrification rate of VMT can be thereby estimated. Fig. 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, whose detailed information is explained as below:

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

[3] For interpretation of color in Figs. 1, 5 and 8, the reader is referred to the web version of this article.

[4] During the simulation, the trip chain in the historical dataset is strictly obeyed. In other words, according to the dataset, if a vehicle's parking time is longer than the needed recharging time, the vehicle will wait outside the charging station after recharging until the parking time ends.

Table 1
Record sample.

ID	Time stamp	Speed	Longitude	Latitude
84471	201411120715	32	116.8198	40.34311

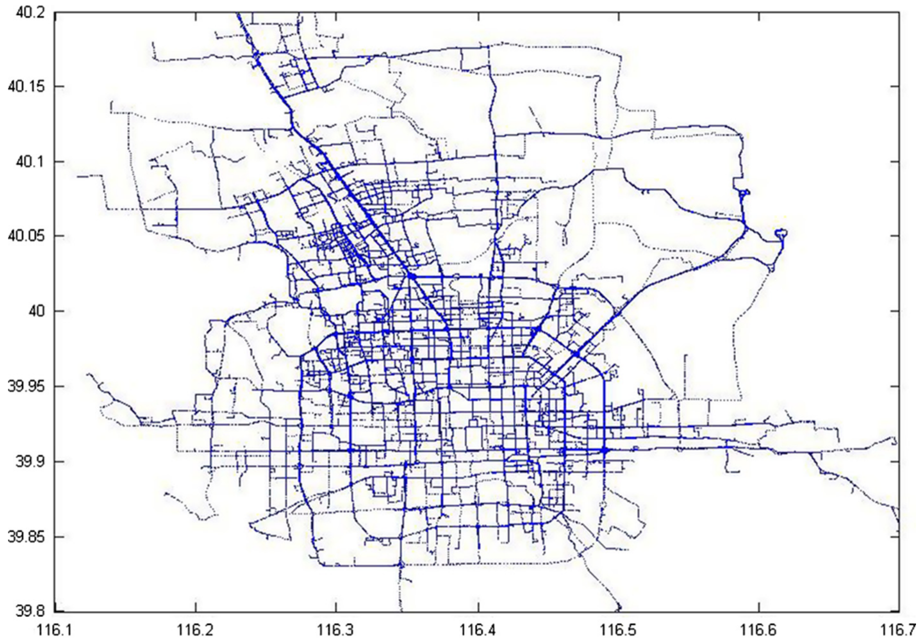


Fig. 1. GPS trajectory sample.

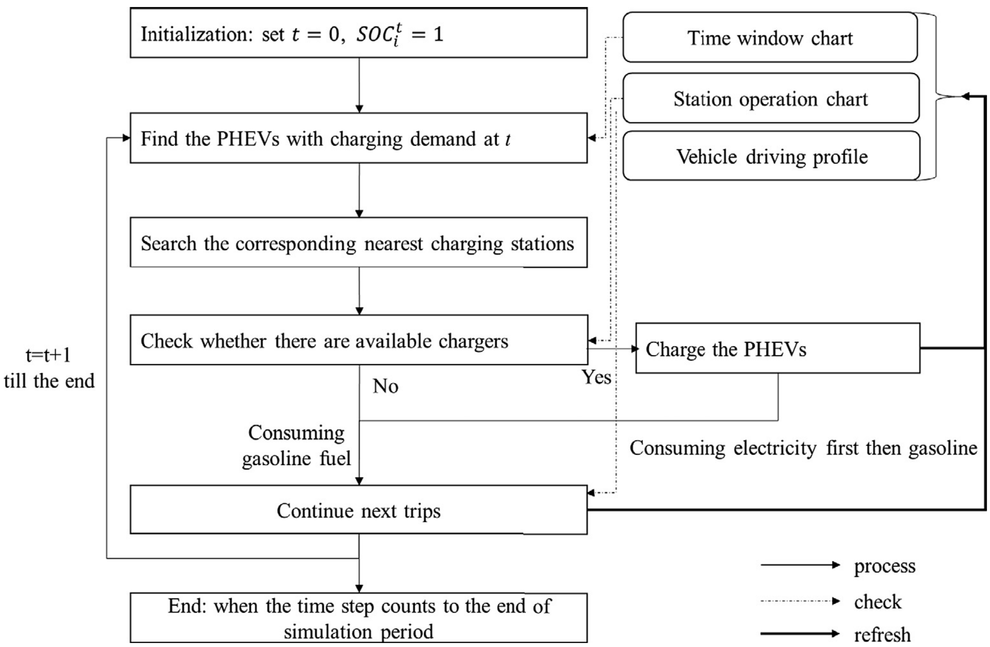


Fig. 2. Simulation model flow chart.

- The vehicle driving profile chart stores the detailed information about 6,519,389 taxi trips, extracted from the taxis' trajectory dataset and including the times and locations of the trips' origins and destinations, the trip distances and corresponding taxi vehicles' IDs.
- The station operation chart describes each charging station's real-time state, whose rows and columns respectively correspond to time steps and station IDs. Each column of the chart records the number of a station's vacant chargers at different times. Note that we update the chart each time a charger is occupied by a PHEV.
- Similar to the station operation chart, the PHEV time window chart, whose rows and columns respectively correspond to time steps and vehicle IDs, is used to describe each PHEV's state at different time to help identify charging demands. This chart is also dynamically updated as the simulation process continues.

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 stations 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.

The details of the simulation model are shown as follows:

Step1: Set $t = 0$, $\mathrm{SOC}_i^t = 1, \forall i$. Choose the time step as five minutes.
Step2: Set the threshold SOC as 0.2. At time index t, find the PHEVs with charging demand, i.e., SOC below 0.2.
Step3: For any PHEV with charging demand, identify its nearest charging station within a predefined distance, which implies that drivers tend to choose the nearest station for recharging.[5] 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.
Step4: Send the PHEV to the identified station. If there is at least one charger available within five minutes since arrival, recharge the vehicle. The recharging time equals the minimum of the time needed to replenish the battery and the remaining time of charging time window. Otherwise, the PHEV will continue its trip, consuming electricity first and then utilizing the gasoline after the electricity is exhausted.
Step5: 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 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. In fact, we find that most of the checks are meaningless because a PHEV driver does not charge when he/she is fulfilling a trip, or the battery's SOC is above the threshold. Inspired by this observation, we introduce a more efficient method, which we refer to as the Tetris method. Specifically, we firstly construct the PHEV time window chart, as shown in Fig. 3. During running the simulation model, we use this chart to assist us to efficiently identify the charging demands of PHEVs. Basically, we use zero to identify the potential time steps when PHEVs may have charging demands. During the simulation, we progressively eliminate the time steps at which PHEVs do not possibly have charging demands. These time steps are marked as -1 in the time window chart, and mainly include the period when PHEVs are fulfilling trips or their battery's SOC is above the threshold. The detailed procedure of the Tetris method is shown as follows:

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.
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 the finish of 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 j.
v. For vehicle k, let C_k represent the number of row where zero firstly 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.

Fig. 3 further illustrates the steps iv and v of Tetris method.

2.4. Public charging station location and intelligent charging guidance system

Public charging stations should be located to 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

[5] 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.

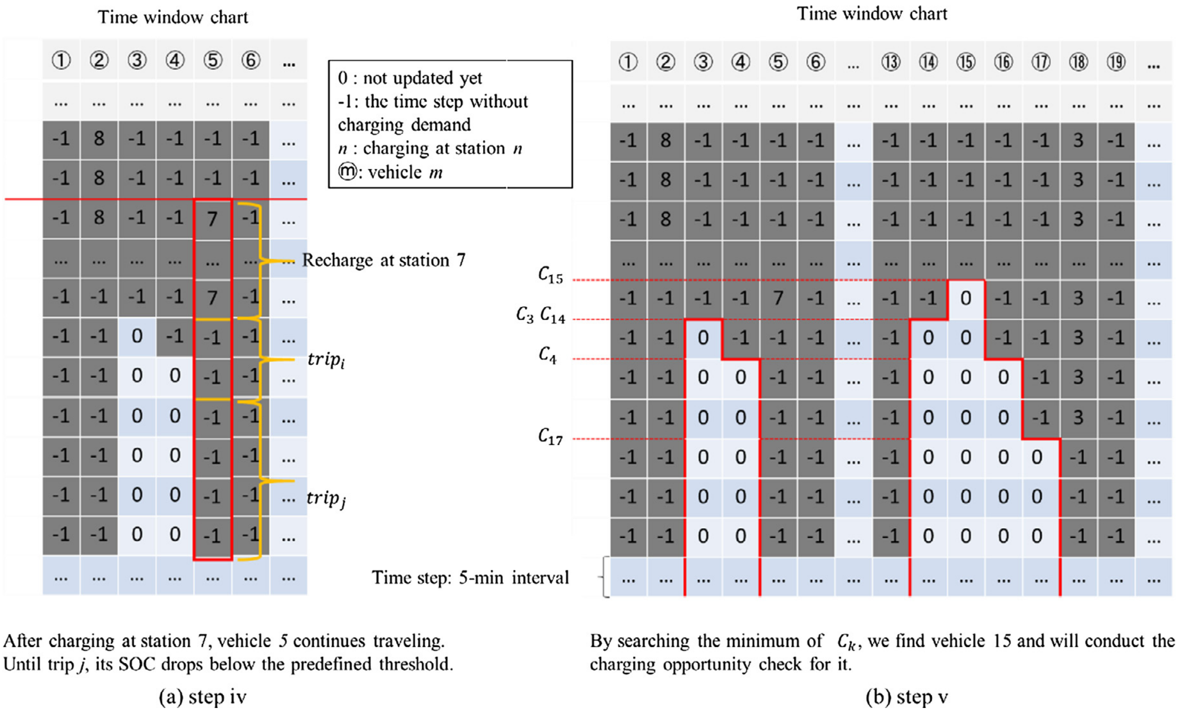


Fig. 3. Tetris method.

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.[6] 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. Fig. 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 that these locations suit the hot spots and parking lots of Beijing well, indicating that the clusters of charging time windows indeed reveal the possible future charging needs.

Recall that in the proposed simulation model, PHEVs with charging demands always choose the nearest stations within a predefined distance to seek for charging opportunities in spite of the utilization levels of the stations, which mostly happens 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 the 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 predefined distance to the vehicle. In Section 3, we will quantify the effects of introducing such a system.[7]

2.5. Simulation environment

To provide guideline 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 (Dong et al., 2013):

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

[7] The strategy of navigating the vehicle to the charging station with the most available chargers within a pre-defined distance is adopted to smooth the charging station utilization. Doing this has two advantages. On one hand, it could increase the other vehicles' possibility of finding available chargers within the pre-defined distance. On the other hand, it contributes to balancing the charging load in the power distribution feeders and revenue levels among different charging stations.

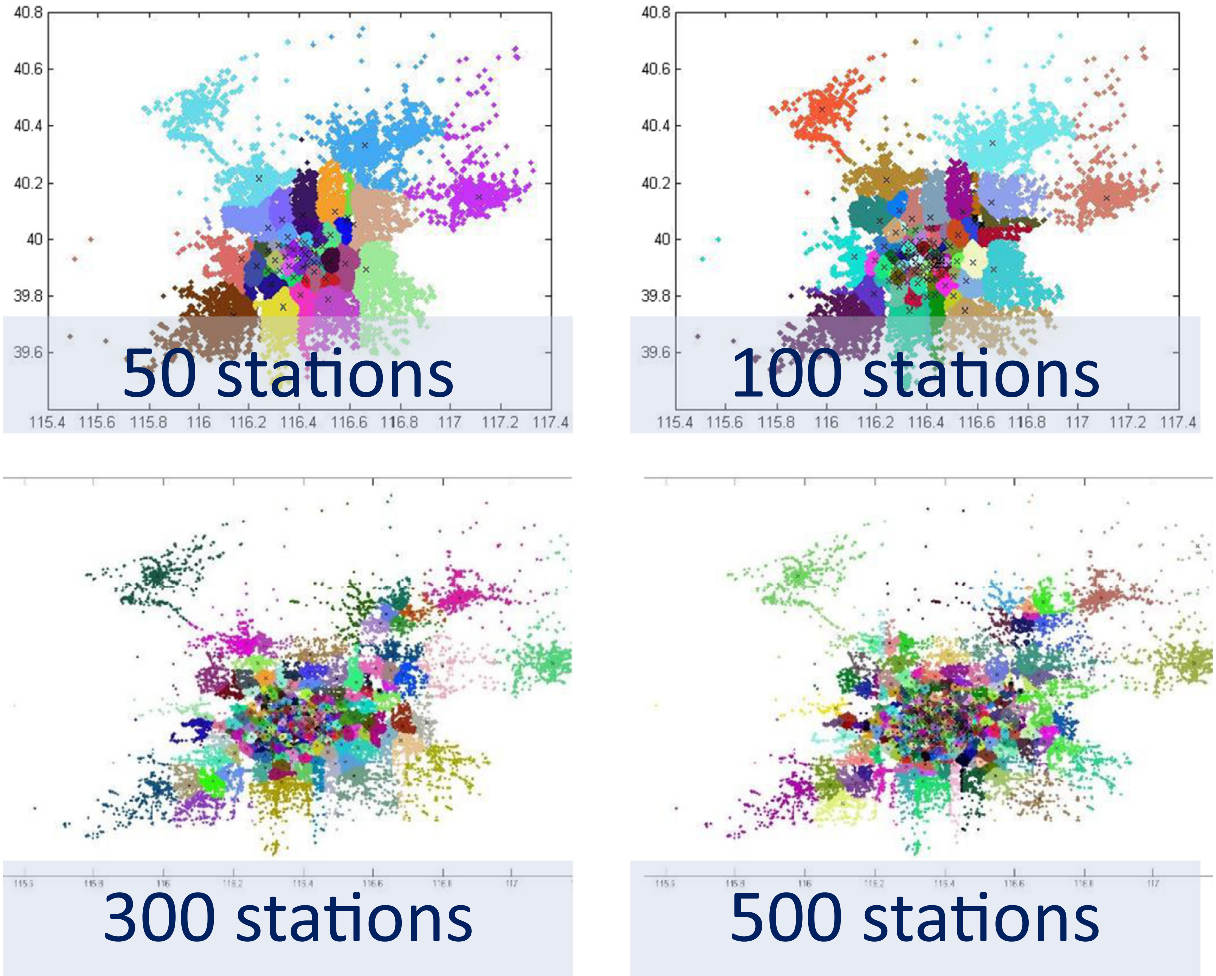


Fig. 4. Location plan of public charging stations.

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
Predefined distance	2km
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 6kW) at each station, no intelligent charging guidance system, battery with the range of 80km, and home charging available.[8] 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.

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

3.1. Simulation results of base scenario

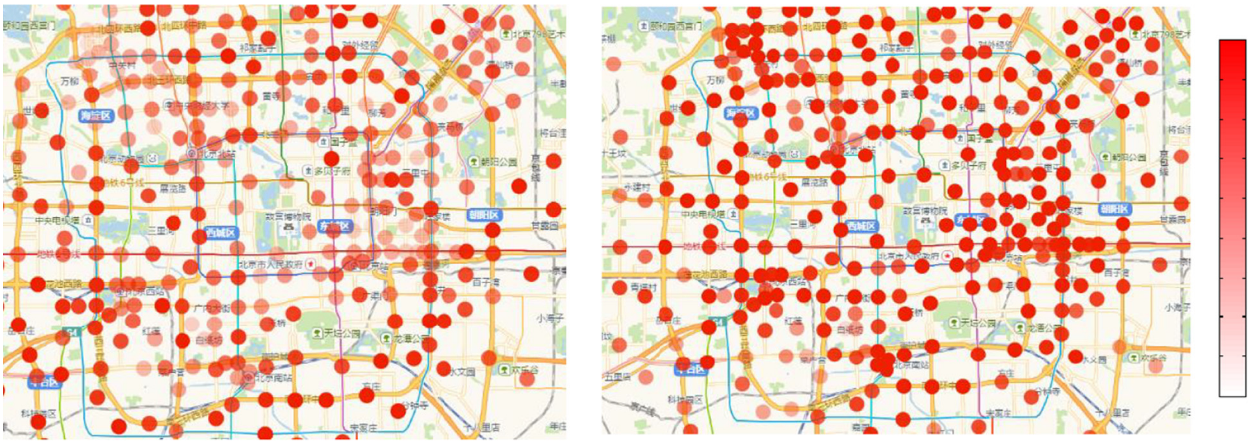
We apply the K-means clustering method to locating the public charging stations. From the simulation results, the electrification rate of VMT reaches 54.3%, equivalent to electrifying 170 million vehicle miles. We also run the simulation with the 500 public charging stations uniformly deployed, and the 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.

Fig. 5 illustrates the average percentage of chargers utilized at midnight and noon respectively during these two months. Each red circle represents a charging station, and its color corresponds to the average percentage of occupied chargers (the depth of the color increases with the percentage 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 because many taxis do not operate during night and hence prefer home charging or the public charging stations in suburban areas.

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

Fig. 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 in it over the amount of energy it can provide in one day (calculated as the total power of chargers multiplied by 24h). From Fig. 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 PHEVs' recharging behavior, revealed in Figs. 5 and 6.

To further reveal the spatial and temporal pattern of charging station utilization level, we select four representative charging stations located in different areas of Beijing to depict their utilization rates during a week. Figs. 8 and 9 demonstrate



midnight noon

Fig. 5. The average percentage of utilized chargers.

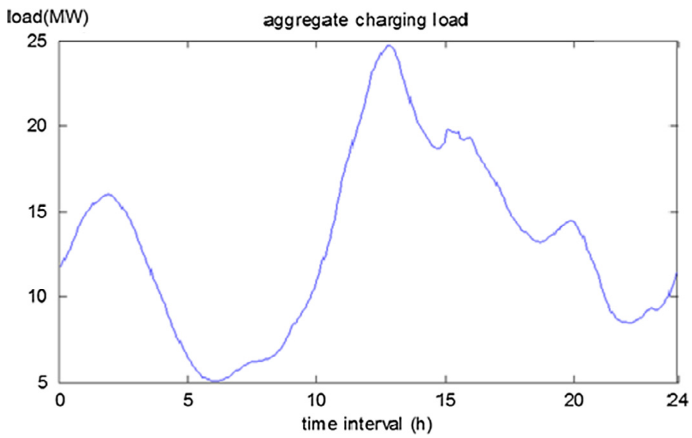


Fig. 6. Daily aggregate average charging power.

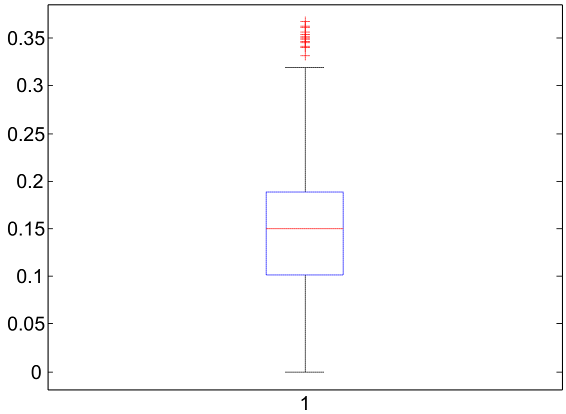


Fig. 7. Distribution of average daily utilization levels for public charging stations.

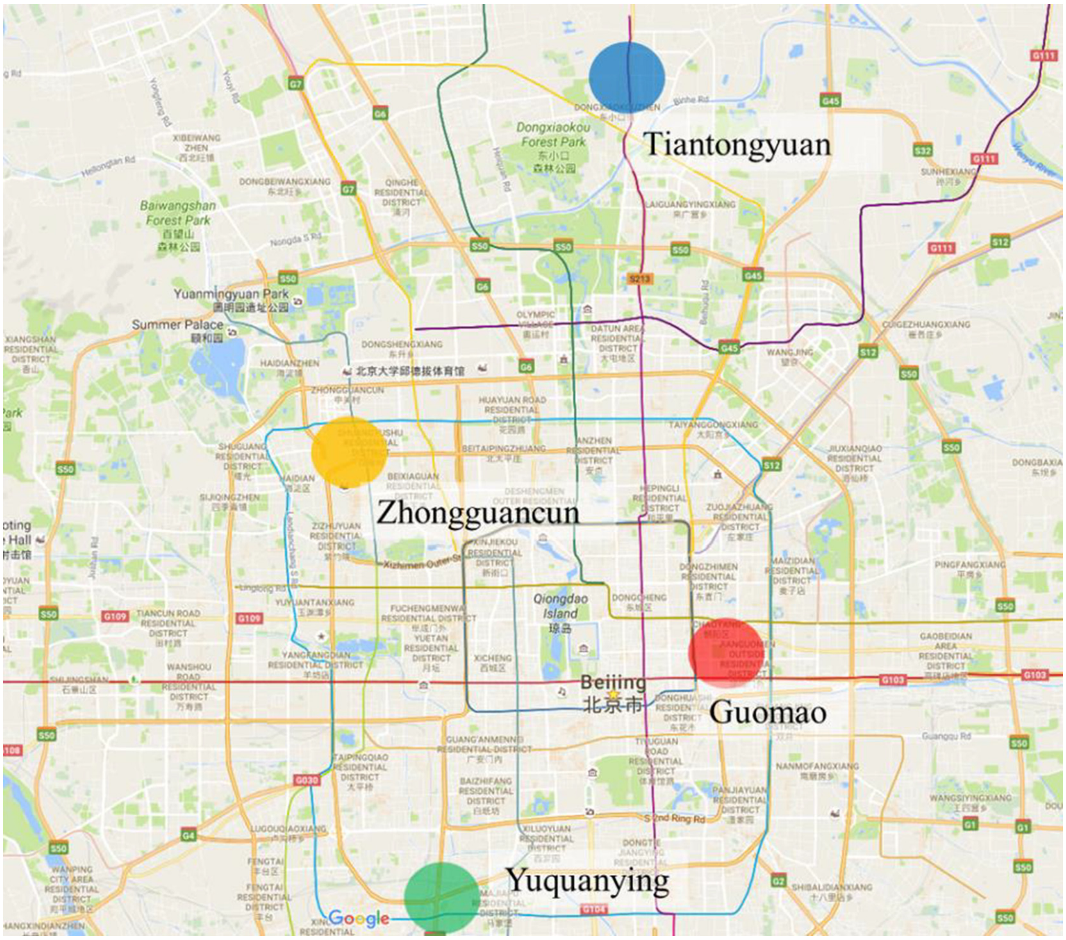


Fig. 8. Locations of the selected charging stations.

their locations and utilization-rate curves, respectively. In Fig. 8, the red circle is located in Guomao area, a financial business district, and the yellow circle is located in Zhongguancun, an area with many high-tech corporations and research institutes. The blue circle is around Tiantongyuan, a suburban residential area, and people living there daily commute to the urban area. The green circle is in Yuquanying area with no large business and residential districts.

From Fig. 9, we can have the following interesting observation:

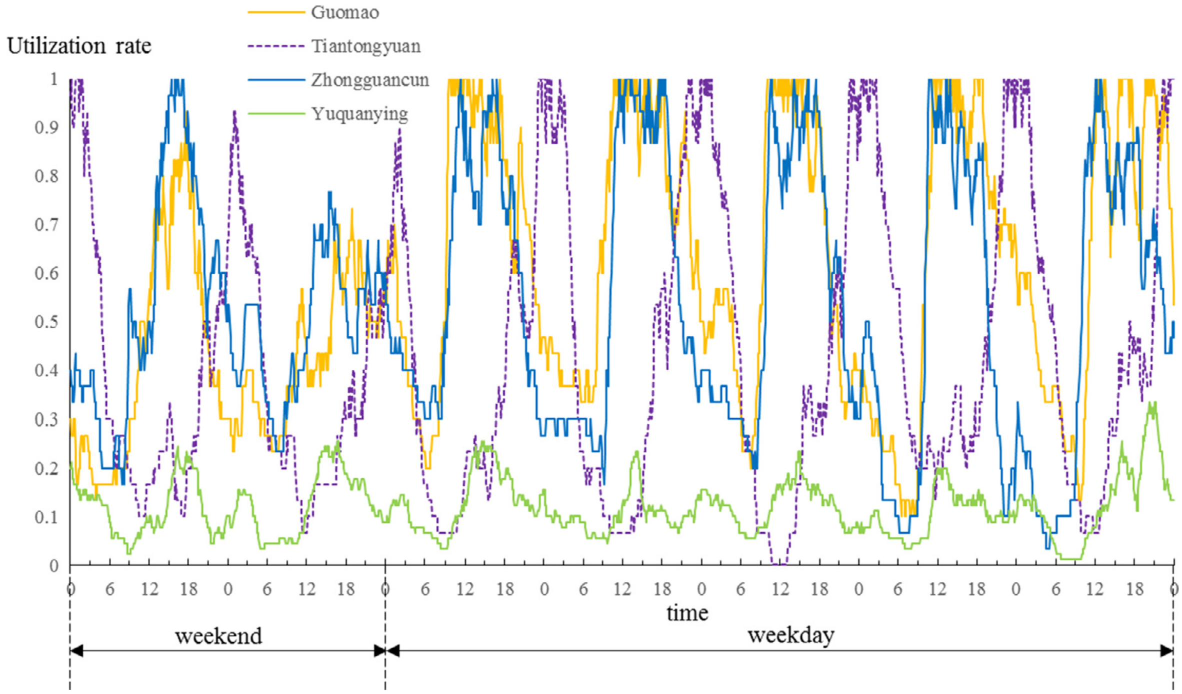


Fig. 9. Utilization-rate curves of charging stations in a week.

- The charging stations in Guomao and Zhongguancun correspond to relatively high utilization rates in weekday. The stations have a high probability to be fully occupied from 12:00 to 18:00, implying that PHEV taxis are likely to drive around these areas in the afternoon, run out of charge and face charging demands.
- Tiantongyuan's charging station's average utilization-rate curve is similar to Guomao and Zhongguancun, except that the peak period is delayed and happens around 24:00, which is possibly attributed to the fact that many taxi drivers take a short rest there at that time and plug in their vehicles in the meantime.
- The average utilization level in weekend is less than weekday. For a particular charging station, the curve owns a similar pattern among different weekdays.
- The utilization rate of Yuquanying's charging station is low, which could be possibly explained because not many taxi trips are originated or destined there.

To explore the impact of the SOC threshold value, we further conduct the simulation investigation, varying the value of threshold from 0.2 to 0.8 and holding other parameters constant. Fig. 10 shows the change of electrification rate. It can be

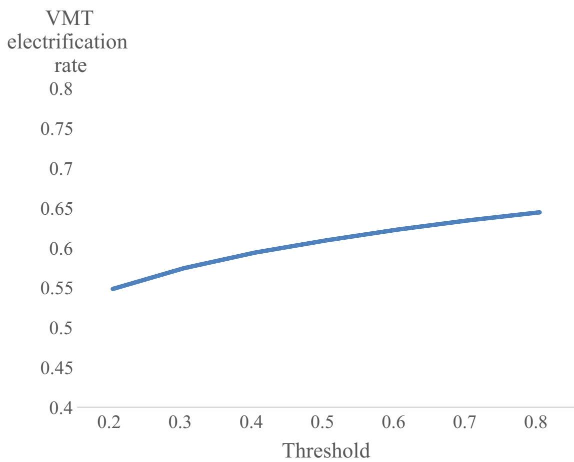


Fig. 10. VMT electrification rate.

observed that the VMT electrification rate increases as the SOC threshold gets higher, which can be explained because a higher SOC threshold means that drivers tend to more actively seek the recharging opportunities during time windows.

3.2. Sensitivity analyses

3.2.1. Home-charging

We firstly evaluate the impact of the availability of home charging on the electrification rate of VMT. Define the electrification gap as the difference between the electrification rates of VMT with and without home charging. Fig. 11 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. But 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 20km, the values of the electrification gaps for all the three plans are below 0.06. In addition, 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.

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 as 500 and setting the total charging power at each station as 180KW (the same as base scenario), Fig. 12 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 30km, 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

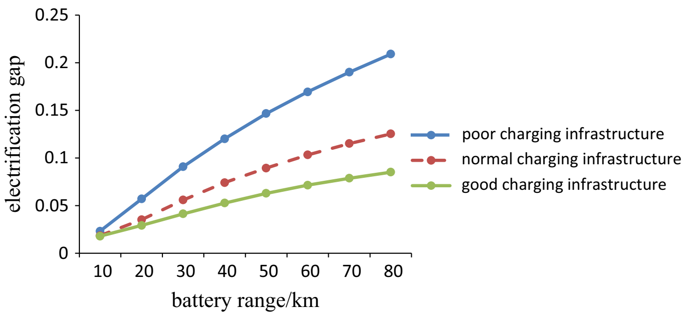


Fig. 11. The influence of home charging.

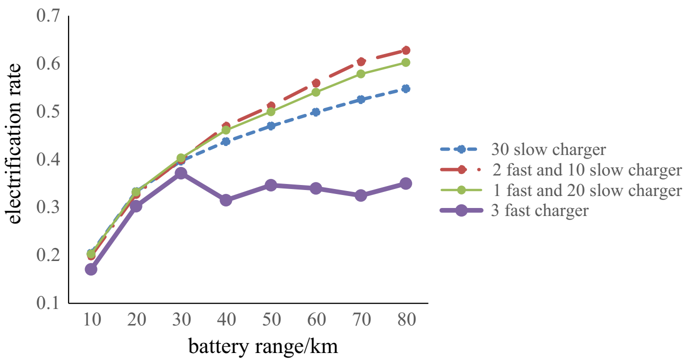


Fig. 12. Impacts of charger types.

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

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, which often happens in business areas. We note that this observation is corresponding to the scenario where PHEV drivers are only willing to wait at most five minutes in stations if there are no chargers available.[9] To summarize, without changing the total power of a public charging station, introducing 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.

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 less 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 Fig. 12, we mix fast and slow chargers at each station. Table 3 shows the charger types and numbers under different station numbers. Fig. 13 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.

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 vehicles. We set the pre-defined distance as 2km. Fig. 14 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 bring an increase of 0.027 by absolute value in the VMT electrification rate because it improves the possibility for PHEVs to find available chargers. Moreover, we also observe that the increase rate is not sensitive to battery range.

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 Fig. 15 through varying the number of slow chargers at each station from zero to 30 and battery range from 10km to 80km. If denoting G, E and N as the electrification rate, battery range and the number of slow chargers respectively, we can observe that $\frac{\partial G}{\partial E} > 0$, $\frac{\partial G}{\partial N} > 0$, $\frac{\partial G^2}{\partial^2 E} < 0$, $\frac{\partial G^2}{\partial^2 N} < 0$. 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 $\frac{\partial G^2}{\partial E \partial N} > 0$, 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.

3.2.6. Dataset validation

The proposed simulation model is based on the trajectory data of taxi fleet. In practice, taxis' trajectories vary from day to day. To explore the impact of such stochasticity embedded in the taxi trajectory data on the electrification rate of VMT, we

[9] We assume PHEV drivers will not wait a long time at charging stations for available chargers in consideration of the following aspects. First of all, 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 rest during the time window. If so, it may not be desirable for them to spend all the dwelling time waiting at public charging stations.

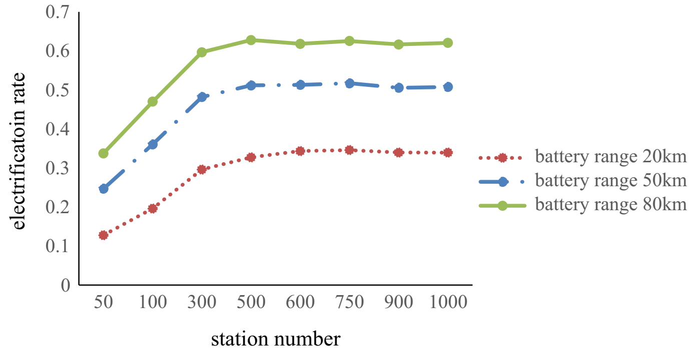


Fig. 13. Impacts of station scales.

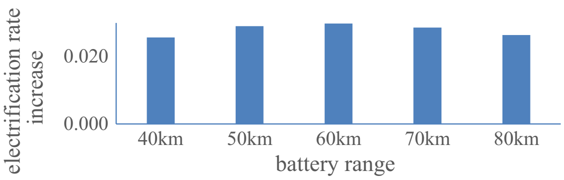


Fig. 14. Impacts of intelligent charging guidance system.

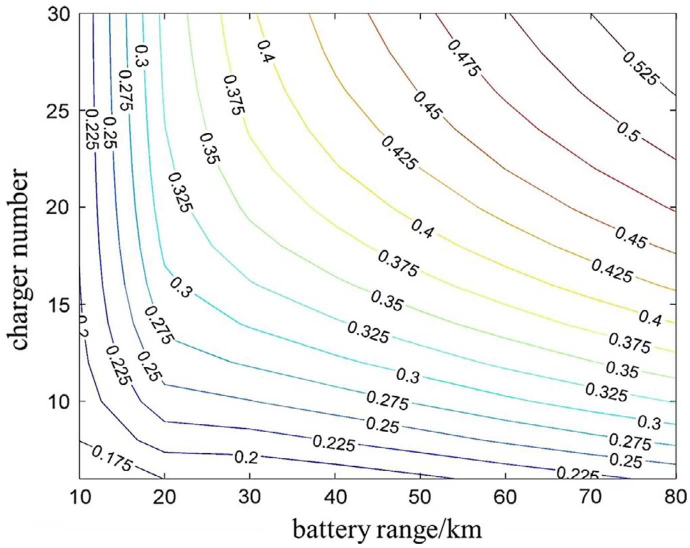


Fig. 15. Contours of electrification rate of VMT.

respectively divide the dataset into eight, four and two components. Each of the eight, four and two components corresponds to one week, half month and one moth of the two moths, respectively. Then, the simulation is run independently for each component to estimate the electrification rate of VMT. Fig. 16 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 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.

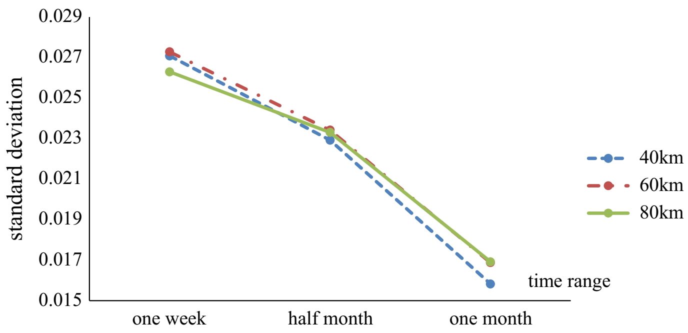


Fig. 16. Impacts of the length of dataset's corresponding period.

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 80km, 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 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 distribute them will increase the electrification rate of VMT but its marginal effect becomes relatively small after the station number exceeds 500.
- Adopting the intelligent charging guidance system can bring an increase of 0.027 by absolute value in the VMT electrification rate
- 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., 2016). 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 to add additional features into the guidance system such as making appointment for charging and predicting the utilization levels of charging stations in the future.

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