A Location Model of EV Public Charging Station Considering Drivers' Daily Activities and Range Anxiety: A Case Study of Beijing

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1 **ABSTRACT**
2 Deploying more public charging stations reasonably is viewed as an important and feasible way
3 by Chinese government to ensure EV consumers to accomplish daily activities without changing
4 their activity schedules, and then to promote the widespread adoption of EVs which is hindered
5 by range anxiety. In this paper, a location model of EV public charging station is proposed by
6 considering daily activities and range anxiety. First, the charging behavior is analyzed and an
7 approach to determine potential charging spot is proposed by considering drivers' demand to
8 accomplish daily activities and the effect of range anxiety. Second, a location model of EV
9 public charging station is presented to minimize the missed trips based on the analysis of the
10 charging behavior. Finally, by using the travel survey data, the characteristics of drivers' daily
11 trips is obtained, and the location model is applied to one of the most prosperous districts in
12 Beijing, China. The result shows that each driver per day makes 2.4 trips, travels 30.1 km, and
13 parks 518 min on average, and only 2.7% of the EV drivers cost more than 50% of the battery
14 capacity. The planning public charging stations cover the areas with commercial, high-tech
15 industry, and universities. Moreover, siting more charging stations could effectively decrease the
16 missed trips, but the effect of the decrease is weakened when the number of charging stations
17 reaches a certain amount, and the regions sited charging stations has a trend to match the top
18 parking regions with the increase of charging stations.
19
21

1. INTRODUCTION

At present, many Chinese cities face the problem of air pollution. In 2014, Beijing suffered 45 heavily polluted days with the Air Quality Index (AQI) being above 200 (*1*). Road transportation sector, which contributes 31.1% of the PM 2.5 in Beijing's air, is widely viewed as one of the main sources leading to the current serious air pollution problem (*2*). Moreover, due to the rapid motorization and urbanization, the transportation sector is likely to remain a large contributor to air pollution, especially in urban areas.

Emerging vehicle technologies are considered as potential solutions for reducing traffic air pollutions, such as electric vehicles (EVs), which could avoid tail pipe emissions and noise, and increase energy efficiency of transportation (*3*). Therefore, the central and local governments of China have set goals for EV adoption. For example, China plans to promote 5 million electric vehicles by 2020 (*4*), and Beijing, as the capital city of China, also plans to promote 600,000 electric vehicles by 2020 (*5*).

However, the widespread adoption of EVs is hindered by the fear that the vehicle may have insufficient range to reach the destination, referred to as range anxiety (*6; 7*). For mitigating the range anxiety of EV drivers, one way is to further enhance the driving range of EVs, but the technology of battery cannot get a breakthrough in a short term. Although some EVs own the driving range around 400km (*8*), the acquisition costs of these EVs are so expensive that cannot be accepted by normal drivers in China. Besides, deploying more public charging infrastructures could be an important and feasible way to ensure EV consumers to accomplish daily activities without changing their activity schedules. Based on the consideration, the government of Beijing plans to build a future-oriented charging network of 435,000 chargers by 2020 (*5*).

With the deployment of public charging infrastructures in many cities, various approaches for siting charging infrastructures are also growing faster. Usually, the first step of these approaches is considering and estimating the public charging demand, which is difficult task due to the lack of realistic EV travel data (*9*). Previous studies use the number of residents (*10*), distribution of gas stations (*11*), and vehicle ownership data (*12*) as proxy for charging demand. However, these methods may not fully reflect the real situation of EV charging demand. First, unlike the gasoline vehicles which only take a few minutes to refuel, EVs can take a much longer time (at least 30min) to fully recharge the battery. Therefore, EVs are more likely to charge at the end of a trip instead of in the middle of a trip (*13*). Second, the charging behavior is impacted by range anxiety, indicating that EV drivers may maintain a comfortable range in case of the EVs being out of battery. Moreover, due to the longer time of charging, EV drivers may determine the charging behavior by considering the daily activities of the whole day, instead of making a decision just for one trip at a time.

Therefore, the objective of this paper is to propose a location model of EV public charging station considering daily activities and range anxiety. The rest of the paper is organized as follows. In Section 2, previous studies about general charging demand estimating method and charging station location model are provided. In Section 3, we analyze the charging behavior is analyzed and an approach to determine the charging spot is proposed by considering the drivers' demand to accomplish the daily activities and the effect of range anxiety. Moreover, a location model of EV public charging station to minimize the missed trips based on the analysis of charging behavior is presented, and a GA (genetic algorithm) based algorithm is presented to site public charging stations. In Section 4, by using the travel survey data, the characteristics of drivers' daily trips is obtained, and the location model is applied to Haidian District of Beijing, China as a case study using the travel survey data. In Section 5, the main conclusions and an outline of future research are provided.

2. LITERATURE REVIEW

In recent years, EVs have been rising in importance. As providing a suitable charging infrastructure network was identified to be a key element for promoting EV adoption, various researchers have focused on the deployment of charging infrastructures. This section briefly reviews two main parts of deployment of charging infrastructure: charging demand estimation and charging station location model.

2.1 Charging Demand Estimation

Due to the lack of realistic EV travel data, some researchers used static statistic data as proxy for estimating charging demand. Kou et al. (2010) use the number of residents to estimate the charging demand (*10*). However, the number of residents cannot fully reflect the number of electric vehicles. Sadeghi-Barzani et al. (2014) use vehicle ownership data as proxy for charging demand (*14*). Frade et al. (2011) use number of residents and the vehicle ownership data to estimate the charging demand (*12*). Liu (2012) uses the distribution of gas stations to estimate the charging demand (*11*). However, the static statistic data cannot fully reflect the dynamic characteristics of the charging demand.

Contrast with the gasoline vehicles which only takes a few minutes to refuel, EVs may take at least 30min to fully recharge the battery, resulting in being more likely to charge at the end of a trip instead of in the middle of a trip. Realizing the charging opportunity at the end of the trip, Namdeo et al. (2014) use trips simulated with OD (origin and destination) pairs to study the charging demand (*15*). Cai et al (2014) use trajectory data of taxis in Beijing to collect the vehicle parking "hotspots" for estimating charging demand (*16*). Chen et al. (2013) use data from household travel survey to estimate the parking demand, and locations with a high parking demand are considered as locations with high potential charging demand (*17*). These studies above are mainly based on the separate trips; however, the charging demand may exist in the successive activities. If an EV driver stops at several different places during the day, a charging station in one of the stops could affect the charging demand in the remaining stops and could lead to a different solution (*9*).

Some researchers realize that the charging demand should be considered with the daily activities and scheduling. Andrews et al. (2013) use the household survey data to estimate whether or not a series of trips can be accomplished by EVs, and the EVs not able to complete their trips have the charging demand (*18*). Dong et al. (2014) assume that drivers of EV should charge the battery at some trip destinations when daily miles exceed the EV range (*6*). He et al. (2015) assume that drivers simultaneously determine tour paths and recharging plans to minimize their travel and recharging time while guaranteeing not running out of charge, and estimate the charging demand on a virtual network (*19*). Cavadas et al. (2015) also consider the chain of activities that each traveler performs to interconnect different demand points (*9*).

Therefore, more research is needed to estimate the charging demand considering the daily activities, especially for a large area. Moreover, range anxiety, which is viewed influencing the charging behavior, should also be considered when estimating the charging demand.

2.2 Charging Station Location Model

Many researchers have focused on the facility location problem for decades. Based on the representation of the demand, the location models could be divided into two types: flow capturing location model and point demand location model.

For the flow capturing location model, the demand is viewed associated with the path of the trip, which is called a flow, and the objective of the model is to site the facilities to capture

the flows as much as possible. In 1990, Hodgson proposes the Flow-Capturing Location-Allocation model (FCLM) (*20*). Kuby and Lim (2005) develop a flow-refueling location model (FRLM) considering the range limitation of the vehicle (*21*). Upchurch et al., (2009) present a capacitated flow-refueling location model (CFRLM), which limits the number of vehicles refueled at each station (*22*).

The point demand location model assumes that the demand is located at distinct places, and the basic unit of the demand is a polygonal area based spatial object in a geographical space (*23*). The representative models includes the p-median problem aiming to minimize the total travel cost (*24*), the p-center problem aiming to minimize the maximum travel cost (*24*), and the maximum coverage location problem (MCLP) aiming to maximize the demand coverage under a certain number of facilities (*25*).

Because the charging time is relative longer, EV drivers are more likely to charge at the end of a trip instead of in the middle of a trip; therefore, the flow capturing location model may be more suitable for stations with less service time. For example, Riemann et al. (*26*) apply the flow capturing location model to the wireless power transfer facilities. Compared to the flow capturing location model, the point demand location model is more suitable for charging stations at destinations with more service time, and the model is applied in many relative studies. Frade et al. (2011) use the MCLP model to site the public charging stations for Lisbon, Portugal (*12*). Asamer et al. (2016) use the MCLP model to select regions for placing charging stations, and the objective of the model is to maximize the sum of covered taxi trip counts (*3*). He et al. present a case study of Beijing, China to compare the optimal locations from three different point demand location models (*27*).

3. METHODOLOGY

To estimate the charging demand, the EV public charging behavior is analyzed and an approach to determine the charging spot is proposed by considering the drivers' demand to accomplish the daily activities and the effect of range anxiety. Then, based on the charging demand determining approach, a location model of EV public charging station is proposed, and a GA (genetic algorithm) based algorithm is presented to site the public charging stations.

3.1 EV Public Charging Behavior Analysis

It is viewed that the charging behavior is derived from the travel behavior, and many researchers tried to analyze the charging behavior based on the travel behavior. Previous studies use the trip-based method to estimate the charging demand; however, this method may cause the repetition of estimating the charging demand (*9*). Because the charging time is relative longer, the EV drivers usually planning the charging behavior by considering the daily activities, instead of charging suddenly while traveling. Especially for public charging behavior, the EV drivers are more likely to charge at the destinations, because it could utilize the time of daily activities and barely cost extra time. In addition, one special characteristics of EV drivers is the range anxiety, which is the fear that the vehicle may have insufficient range to reach the destination (*7*), and could inevitably affect the drivers charging behavior. For avoiding the range anxiety, the drivers usually maintain a comfortable range, which means the minimal range for the drivers to feel comfortable while driving. The comfortable range indicates that the drivers prefer to charge when the state of charge (SOC) is lower than the comfortable range. Previous studies conclude that the comfortable range could reflect as an absolute value, a relative value, or a minimum value (*28*).

For considering the daily activities, the trip-chain of the EV drivers is treated as the base

1   unit for analyzing. Moreover, the trip-chains in weekday are chosen because of being more
2   regular. The origin and the destination of a trip-chain in the weekday are both the home, and the
3   trip-chain usually has a destination which is the workplace.
4   When making the charging plans, the EV drivers tend to maintain the daily activities (e.g.
5   charging at the destinations and the charging time is less than the activity time). Moreover, the
6   drivers should keep a comfortable range as a threshold to mitigate the range anxiety. Previous
7   studies usually determine a SOC threshold, and when the SOC is lower than the threshold, the
8   EV drivers have the charging demand (*29*).
9   On the basis of the analysis, the charging behavior process of the EV driver is shown as
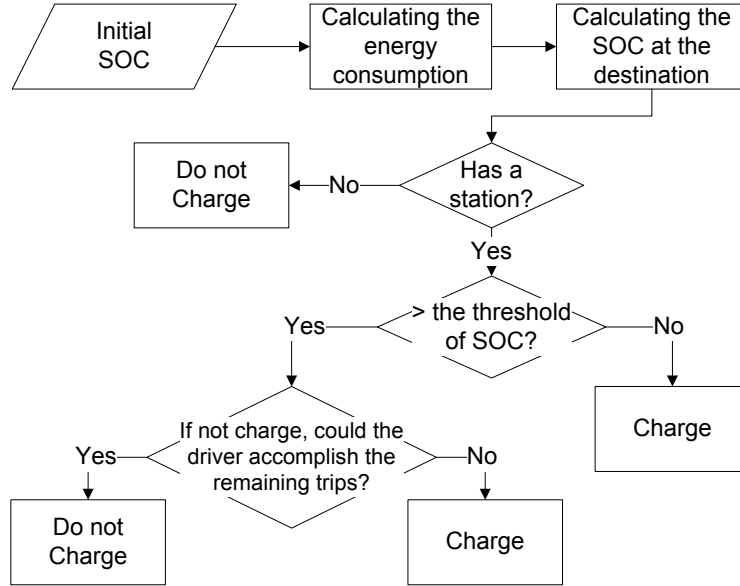10 FIGURE 1.
11

12
13
14 **FIGURE 1 Charging behavior process of EV drivers considering daily activities and range**
15 **anxiety.**
16
17   As shown in FIGURE 1, the drivers first obtain the SOC of the EV at the destination
18 based on the initial SOC and the energy consumption. Then, based on the SOC at the destination,
19 the station condition (whether or not the destination has a public charging station), the threshold
20 of SOC, and the demand to accomplish the remaining trips, the drivers will make the finally
21 decision to charge at the destination or not. It is noted that although the SOC is larger than the
22 threshold, the drivers also need to determine whether or not to charge at the destination. If the
23 drivers do not charge and cannot accomplish the remaining trips under existing conditions, they
24 still need to charge at the destination.
25   If the drivers choose to charge at the destination, the charging time is as long as possible
26 (*30*). Moreover, considering that the drivers are not likely to charge when the parking time is too
27 short, similar to Cai et al., (2014), a threshold of fifteen minutes parking time is used to separate
28 the trips (*16*).
29
30 **3.2 A Location Model of EV Public Charging Station**
31 In this section, a location model of EV public charging station is proposed. In the model, the
32 match degree between the charging demand and the public charging stations is concerned, and
33 other factors, such as the power supply and the space, are not considered. For this reason, the

1 regions instead of exact locations for building the public charging stations are selected, and then
2 based on the recommended regions, the exact location of the public charging station within the
3 region could be determined by considering other factors.
4   The EV public charging station location model is given by Eqs. (1)-(2).

5
$$\min f(x) = \sum_j Y_j \tag{1}$$

6   Subject to:

7
$$\sum_{i \in I} x_i = p \tag{2}$$

8 where I is the set of candidate regions for building public charging stations; J is the set of the EV
9 drivers. Y_j is the number of missed trips of driver j. The variable refers to Dong et al. (2014)(*6*).
10 If the remaining range cannot support the EV to finish the trip, the trip is considered as a missed
11 trip, and the subsequent trips are also missed. x_i is a decision variable, and if a charging station is
12 built in candidate site i, then x_i =1; otherwise, x_i =0; p is the number of public charging stations to
13 be built.
14   The objective of the model is to minimize the missed trips on the condition of the fixed
15 number of public charging stations. Considering the analysis in subsection 3.1, the missed trips
16 (Y_j) could be calculated, as shown in Eqs. (3)-(6).

17

18
$$E_j(k) = \min((1 - SOC_j(k)) \cdot BC_j, P_i t_j(k)) \tag{3}$$

19
$$SOC_j(k) = SOC_j(k-1) + \frac{E_j(k-1) - EC_j(k)}{BC_j} \tag{4}$$

20
$$EC_j(k) = d_j(k) \cdot EF_j \tag{5}$$

21
$$Y_j = \sum_{k=1}^{K_j} y_j(k) \tag{6}$$

22

23 where K_j is the number of trips of driver j; $EC_j(k)$ is the energy consumption of driver j's trip k,
24 kWh; $d_j(k)$ is the distance of driver j's trip k, km; EF_j is the energy consumption factor of
25 driver j's EV, kWh/km; BC_j is the battery capacity of driver j's EV, kWh; $t_j(k)$ is the parking
26 time at trip k's destination of driver j, h; $E_j(k)$ is the energy increase of the battery from the
27 recharge at the destination of driver j's trip k, kWh; $SOC_j(k)$ is the SOC at the destination of
28 driver j's trip k, %; P_i is the charging power at candidate site i, kW. If x_i=0, P_i=0; $y_j(k)$ is a
29 decision variable. If driver j's trip k is a missed trip, then $y_j(k)$=1; otherwise, $y_j(k)$=0. If
30 $SOC_j(k)$<0, which indicates that driver j could not complete trip k and the subsequent trips, then
31 $y_j(k)$=1, and $y_j(k+1) \ldots y_j(K_j)$ also assign to one.
32   To solve the EV public charging station model, Genetic Algorithm (GA) based
33 optimization model can be applied to minimize the objective function of the location model
34 subject to the constraint. GA (*31*) could globally find the optimal solutions for complex
35 optimization problems by simulating the natural behavior, and is applied to many charging
36 station location problems.
37

4. CASE STUDY

4.1 Data description
The data is obtained by Beijing Household Survey in 2014, including 40,000 families with 180,000 people. In the survey, each respondent should record the daily trips with sufficient information, such as the start and the end time, the locations and the types of the origin and the destination, the travel distance, the purpose, and the traffic mode. Haidian District, one of the most prosperous districts in central area of Beijing, China, is selected as the study area, whose area is 430.8km^2 and the population is 3.28 million. This district includes Zhongguancun, which is often called as "China's Silicon Valley", Shangdi, which is high-tech industry area, Century City, which is a commercial and residence mixed area, and many famous universities (e.g., Tsinghua University and Peking University).

There are 2415 sample drivers having destinations in the study area with 5750 trips. Based on the sample rate, the sample drivers in the study area represents for 25,000 drivers with about 60,000 trips. Based on the EV promotion goal of Beijing (600,000 EVs in 2020 (*5*) and the vehicle ownership will be 6,300,000 in 2020 (*32*)), the EV adoption rate is set to be 10%; therefore, there are totally 2,500 EV drivers (25,000*10%=2,500, hereinafter referred to as "the EV drivers") in the study area, which contains the study dataset.

4.2 Results and discussion
In this section, first, the preliminary statistics are summarized to reveal the characteristics of the drivers and their daily trips based on the study dataset. Second, the location model of EV public charging station is applied to site the public charging stations in the study area, and then the result is analyzed.

4.2.1 Preliminary statistics
Based on the study dataset, some basic statistics are obtained first to reflect the characteristics of the drivers and their daily trips, including basic trip characteristics, the distribution of EV drivers' residences, the daily energy consumption, the parking time and the proportion of trips under different activity types, and the distribution of parking demand (potential charging demand).

The basic trip characteristics of the EV drivers show that each driver makes 2.4 (Median = 2, Standard Deviation (SD) = 0.9) trips, travels 30.1 (Median = 24.6, SD = 26.7) km, and has a total parking time of 518 (Median = 540, SD = 143.8) min per day. The number of trips per day indicates that in weekday the EV drivers often have a trip-chain built by two trips, whose typical type is home-workplace-home, which has a proportion of 79.2% of all the EV drivers. Due to the statistics of the EV drivers' residences, the EV drivers mainly live in the study area (61% of the EV drivers). Moreover, about 34.5% of the EV drivers live in the areas adjacent to the study area, and only 4.5% of the EV drivers are from other areas.

BAIC(Beijing Automotive Industry Corp.) E150, one of the most popular EVs in Beijing, is chosen as the typical electric vehicle, which has a battery capacity of 25.6 kWh and an energy consumption factor of 0.15 kWh/km. Based on the BAIC E150, the daily energy consumption of the drivers on average is 4.5 (Median = 3.7, SD = 4.0) kWh per day. For fully comparing the daily energy consumption and the battery capacity, the distribution of the EV drivers' daily energy consumption level, which is the ratio of the daily energy consumption to the battery capacity of the EV, are summarized (as shown in FIGURE 2).
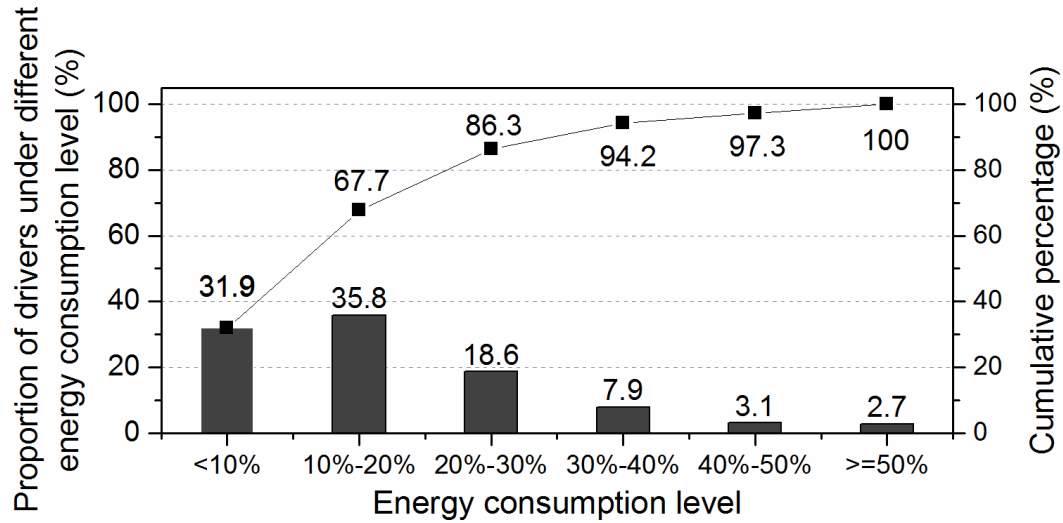
FIGURE 2 Pareto chart of distribution of drivers' daily energy consumption level.

In FIGURE 2, only 2.7% of the EV drivers could cost more than 50% of the battery capacity to finish the daily trips, and the majority (67.7%) of the EV drivers could cost less than 20% of the battery capacity per day, indicating that the battery capacity of EVs could roughly cover the daily trips. However, this conclusion is based on the EVs with full battery capacity. In reality, the EV drivers in Beijing may not be able to have a private charger and charge every day because of the Land shortage, resulting that the public charging stations are necessary for guaranteeing the charging supply.

The parking time, which may be determined by the type of the activity, could be the potential time to charge the EV. In this paper, the activities are divided into three types: subsistence (e.g. work and study), maintenance (e.g. repast, go shopping, and pick up), and discretionary (e.g. entertain and visit friends) (*33*). The subsistence trips and discretionary trips have a parking time with 518.2 min and 220.2 min on average, indicating that the drivers may have enough time to charge the EVs. Compared to the subsistence and the discretionary, the maintenance trips only have a parking time of 58.3 min on average; however, the drivers could still utilize these time to charge the EVs. Moreover, the proportion of subsistence trips is 72%, indicating that the drivers often travel to work or study in weekday. The proportion of maintenance trips (22.9%) is less than that of the subsistence, and the proportion of discretionary trips is only 5.1%, which is a minor activity in terms of the quantity. The result indicates that in the case study the EV drivers could utilize the parking time at the destination of the trip to charge in weekday, especially the subsistence trips, which are major trips and have a longer parking time.
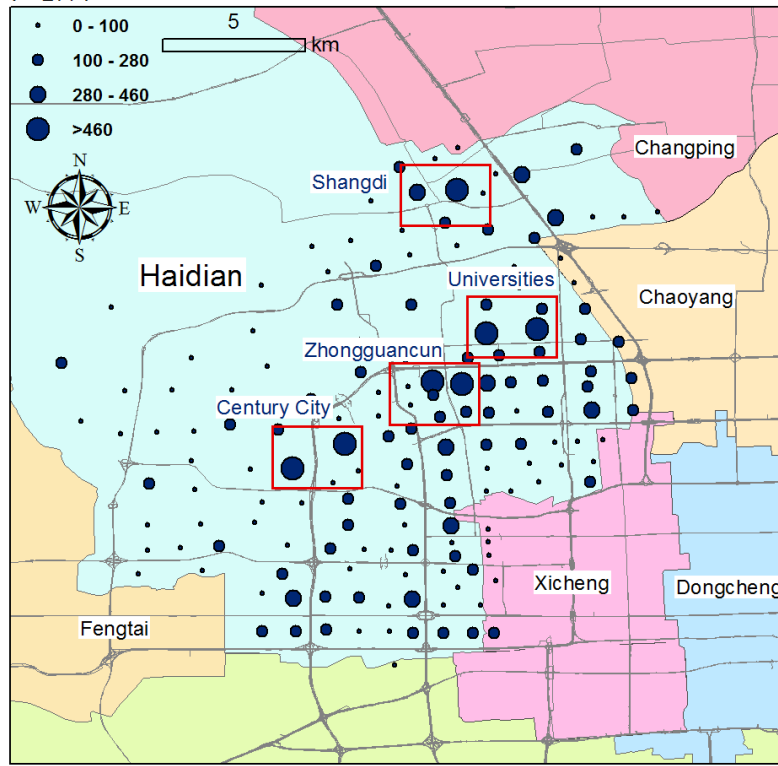
FIGURE 3 Distribution of potential charging spots.

The destination with more parking vehicles may be a potential charging spot (*6*). On the basis of this statement, statistics of the potential charging spots based on the drivers' destinations and parking times are obtained (the trip whose parking time is less than 15min is excluded due to subsection 3.1), as shown in FIGURE 3. The largest potential charging spots mainly locate in some commercial areas and universities, such as Zhongguancun, Shangdi, Century City, Tsinghua University, and Beijing Language and Culture University. Among these spots, Zhongguancun is Beijing's center of technology, talent, and information, and also has a large potential charging demand.

4.2.2 Charging Station Planning
Using the study dataset and the EV public charging station location model, the planning result of the public charging stations is obtained. Considering that the parking time at public charging stations is usually less than that at home, the drivers tend to choose fast chargers at public charging stations; therefore, only the fast chargers (20kW) are considered. Moreover, the EV model is based on BAIC E150, whose battery capacity and energy consumption factor are 25.6kWh and 0.15kWh/km, respectively. In addition, the threshold of SOC is set to be 0.3 based on the analysis in subsection 3.1, and the initial SOCs of EVs are assigned randomly from 0.3 (the threshold of SOC) to one.
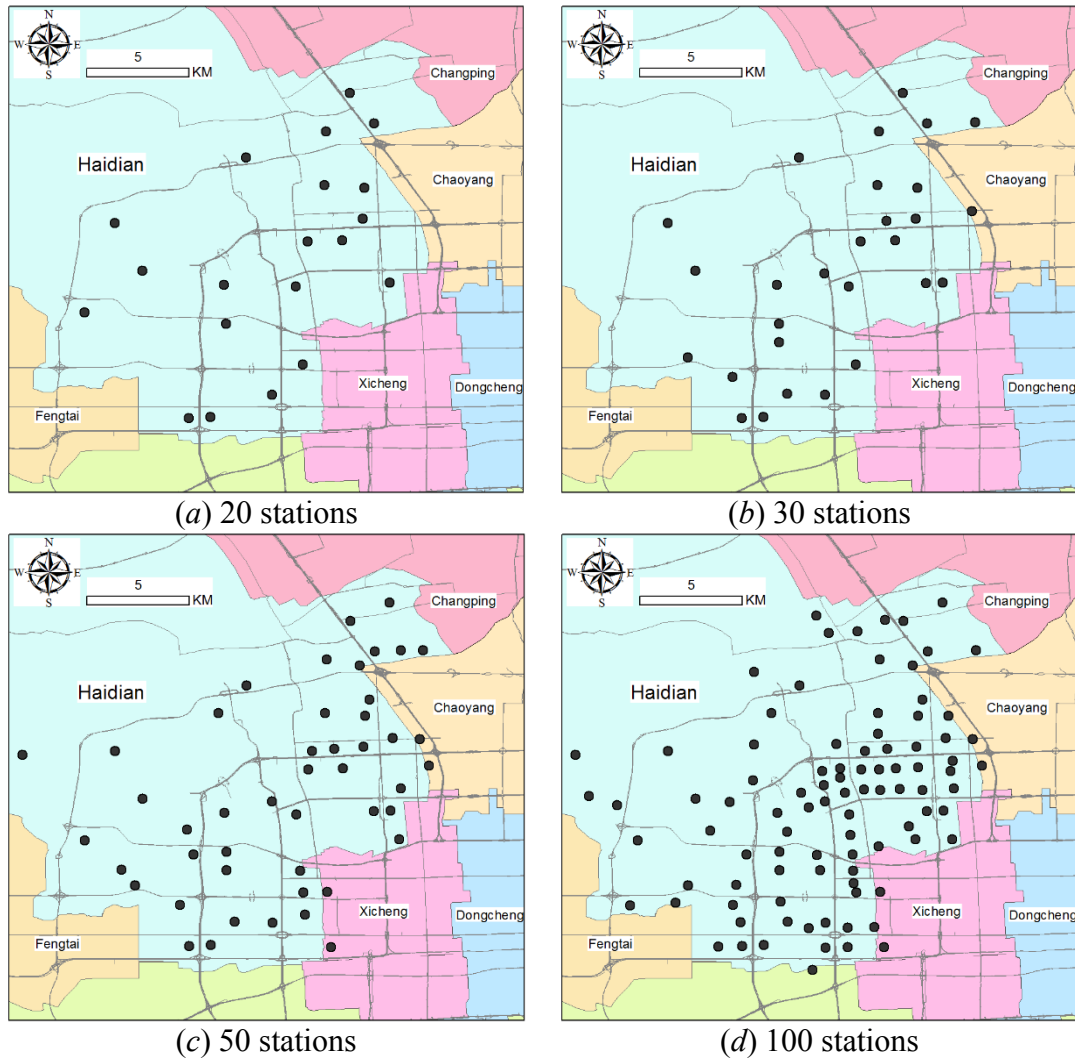
(*a*) 20 stations

(*b*) 30 stations

(*c*) 50 stations

(*d*) 100 stations

1
2   **FIGURE 4 Locations of the planning public charging stations with different total numbers.**
3
4   The locations of the planning public charging stations cover the main regions (e.g.
5   Shangdi, Zhongguancun, Century City, and some universities) in Haidian district, and expand to
6   other regions gradually as the number of public charging stations increasing (FIGURE 4*a-d*).
7   To evaluate the missed trip declining effect of the public charging stations, the declining
8   rate is defined as Eq. (7).
9

10    $$DR = \frac{MT_0 - MT_p}{MT_0}$$ (7)

11
12   where *DR* is the declining rate, MT_0 and MT_p are the numbers of missed trips when the number
13   of public charging stations are 0 and *p*, respectively.
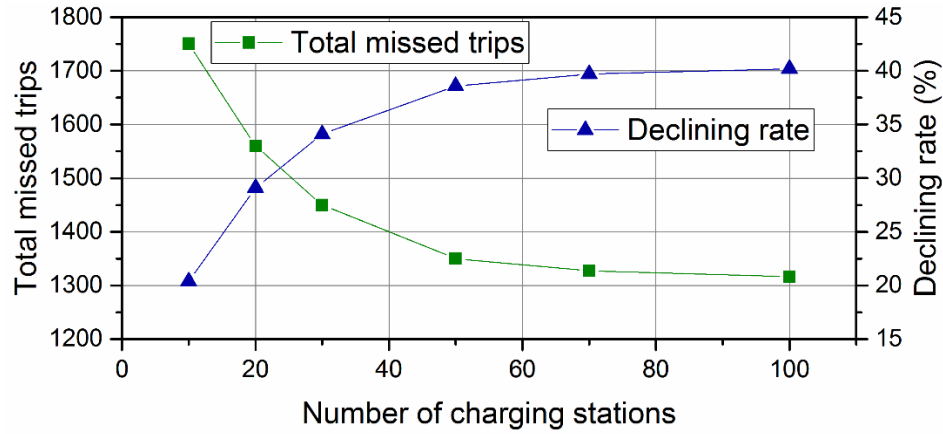14

FIGURE 5 Variation of missed trips and declining rates under different numbers of public charging stations.

The variation of missed trips and declining rate under different numbers of public charging stations is shown in FIGURE 5. The missed trips (green line) decline initially but stay stable when the number of public charging stations is 50 or more. The declining rate is lower at first, and then increases with the increase of the number of public charging stations, and stays stable when the number of public charging stations is 50 or more. The result shows that siting more public charging stations could effectively decrease the missed trips when the number of charging stations is less; however, when the number of public charging stations reaches a certain amount (50 stations in the case study), the effect of the decrease is weakened.

Previous studies assume that the region with more parking vehicles should be a charging station. However, when siting the public charging stations in this paper, not only the parking place (destination), but also the daily activities as a whole are considered. To compare the match degree between the regions of planning public charging stations (FIGURE 4) and the regions with more parking vehicles (FIGURE 3), the *SP* ratio is presented, which is defined as Eq. (8).

$$SP_p = \frac{Card(A_p \cap B_p)}{Card(B_p)} \tag{8}$$

where SP_p is the *SP* ratio when the number of charging stations is p; *card*() is the function to count the number of the set elements; A_p is the set of the regions sited the public charging station when the number of charging stations is p; B_p is the set of the top p regions with the most parking demand.
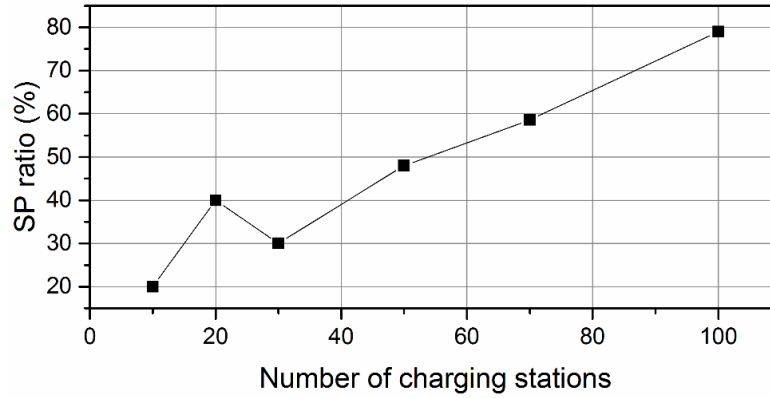
FIGURE 6 Variation of SP ratios under different numbers of public charging stations.

FIGURE 6 shows the variation of *SP* ratios under different numbers of charging stations. The *SP* ratio of 10 charging stations is 20%, while that of 100 charging stations reach 80%. As a whole, the *SP* ratio raises with the number of charging stations increasing. The result shows that the regions of the charging stations do not well match the top parking regions when the number of charging stations is less, and the regions sited the charging stations has a trend to match the top parking regions with the increase of the number of charging stations. The *SP* ratio is lower at first is because the objective of the location model (minimize the missed trips) is not in accord with the parking demand, which indicates that not only the parking demand but also the charging behavior and the daily activities should be considered when siting of the charging stations.

5. CONCLUSIONS

In this paper, a location model of EV public charging station is proposed by considering daily activities and range anxiety. First, the charging behavior is analyzed and an approach to determine potential charging spot is proposed by considering the demand of EV drivers to accomplish the daily activities and the effect of range anxiety. Second, a location model of EV public charging station is presented to minimize the missed trips based on the analysis of charging behavior, and a GA (genetic algorithm) based algorithm is applied to site the public charging stations. Finally, by using the travel survey data, the characteristics of drivers' daily trips is obtained, and the location model is applied to Haidian district of Beijing, China as a case study. The result shows that each driver makes 2.4 trips, travels 30.1 km, and has a total parking time of 518 min daily on average. Only 2.7% of the EV drivers cost more than 50% of the battery capacity to finish the daily trips, and the majority (67.7%) of the EV drivers could cost less than 20% of the battery capacity per day. Moreover, the distribution of potential charging spots based on the parking demand is obtained, which mainly covers some commercial areas and universities. The result of the location model shows that the planning public charging stations cover the areas with commercial, high-tech industry, and universities in the case study. In addition, siting more charging stations could effectively decrease the missed trips, but the effect of the decrease is weakened when the number of charging stations reaches a certain amount. Furthermore, the regions sited the charging stations has a trend to match the top parking regions with the increase of the number of charging stations.

There are several extensions to the study. We assume that the EV drivers are willing to maintain the current activities and destinations, which could also be a goal for the government and the charging industry when establishing the network of charging stations. However, due to

the limitation of driving range and the condition of current charging stations, the EV drivers may make detours and change their activities or destinations when traveling. Therefore, more observations and analysis of EV drivers' travel and charging behavior are necessary in the future. Furthermore, based on the spatial and temporal distribution of charging behavior from the study dataset, the allocation of the chargers in each charging station could be obtained by considering the level of service.

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