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Seasonal Variance in Electric Vehicle Charging Demand and Its Impacts on Infrastructure Deployment: A Big Data Approach

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Abstract

Electric vehicle (EV) charging demand is an essential input of charging facility location models. However, charging demand may vary across seasons. In response, this paper first provided insights into the seasonal variance in charging demand using a unique GPS trajectory dataset which contained travel, parking, and charging information of 2,658 private EVs in Beijing. The dataset was collected in January, April, July, and October 2018, which were representative months in winter, spring, summer, and autumn, respectively. Through statistical and spatiotemporal analyses, we found that in winter, EVs got recharged when their state of charge (SOC) was lower: the average SOCs on working days were 51.96%, 48.39%, 50.86%, and 43.50%, in spring, summer, autumn, and winter, respectively. Furthermore, the central urban areas tended to have a higher charging demand in winter. To further explore how the seasonal variance in charging demand may influence infrastructure deployment, we used the classical p-median model to deploy charging facilities with the charging demands in the four seasons, considering the modifiable areal unit problem (MAUP). The results suggested that the seasonal variance did influence the layout of charging facilities under different spatial analysis units (SAUs). The deployment of charging facilities in the central urban areas and outer suburbs tended to be more sensitive to seasonal variance in charging demand. The findings are expected to be useful for charging infrastructure planning in both the transport and power sectors.

Keywords: Electric vehicle; Charging infrastructure deployment; Seasonal variance; GPS trajectory data

1. Introduction

Reducing carbon emissions has become an essential environmental management strategy in many countries around the world as the threat of subsequent climate change to humans and even the planet's ecosystems have been extensively documented in numerous studies (Hansen et al., 2013; Lee et al., 2017). The transportation sector, one of the major contributors to greenhouse gas emissions, has been a primary target of optimization for the sake of environmental sustainability doubtlessly (Johnson, 2010). Electric vehicles (EVs) labelled as environmentally friendly, less noisy, lower maintenance and better energy efficient have therefore gained extensive attention despite many other possible solutions proposed.

The EV penetration rate is on the rise. On one hand, this is attributed to the continuous progress in material science, electronic science and manufacturing, which results in the fast pace of development of on-board battery energy technology and subsequent large-scale adoption of EVs. On the other hand, people's increasing awareness of environmental protection also accelerates the robust growth of EVs (Doucette & McCulloch, 2011; Li et al., 2019; Thomas, 2009). As reported by the International Energy Agency (IEA, 2022), the global EV stock has boomed from less than 200 thousand in 2012 to more than 16 million in 2021. Additionally, EV sales in 2021 were approximately 30 times higher than that in 2012, reaching 6.6 million. With over half the sales contribution, China sold around 3.3 million EVs in 2021 while it launched its EV pilot program in just 2009 (Jin et al., 2021). Moreover, not only China has proposed a long-term vision for EV development, but also other major contributors to the global EV market such as the US, UK, and EU have also proposed their own EV development plans, with an estimated global EV stock of 120 million by 2030 (Chen et al., 2020; GOSC, 2020; IEA, 2022; Klingel & von Loesecke, 2022; OLEV, 2013).

Nevertheless, with the rapid development of EVs, more demands have been imposed on their charging infrastructure which plays a significant role in the practical application of EVs. In 2021, around 500 thousand new public chargers were installed worldwide, compared to a total of 430 thousand in 2017, which brings the total to 1.8 million (IEA, 2017, 2022). However, unlike internal combustion engine vehicles (ICEVs) that can get refuelled in a few minutes, EVs usually need to take several hours for charging in the early stage due to the low-power chargers. Owing to the swift advancement of charging technology, there has been a variety of fast chargers with different power specifications as well as super-fast charging with over 100 KW power, which has achieved a great reduction in the users' charging time (Deb et al., 2021). In the future, over 1 billion dollars are expected to be invested in public charging facilities in the US by 2025 and 7 million charging stations would be set up in France by 2030 when the global amount of charging infrastructure would have more than twelve-fold increment (IEA, 2022; Metais et al., 2022; Nicholas, 2019).

Lots of efforts have been put into the deployment of charging infrastructure, so as to meet the rising charging demand. However, previous charging facility location models tended to use charging demand within a fixed period (e.g., one month) as model input, and paid little attention to the seasonal variance in charging demand caused by the effect of weather and temperature on on-board battery performance. It is widely accepted that the energy consumption of EVs rises notably in cold weather compared to usual ambient temperatures (Donkers et al., 2020; Fetene et al., 2017; Koncar & Bayram, 2021). This would further influence the travel and charging patterns of EV users (Hao et al., 2020; Järv et al., 2014).

In response, this paper first provides insights into the seasonal effect on EV charging demand and further explores how neglecting the variance in charging demand could influence the subsequent infrastructure deployment. In particular, we use a unique GPS trajectory dataset that contains the travel, parking and charging information of 2,658 private EVs in Beijing. The dataset was collected in January, April, July, and October 2018, which are representative months in the four seasons, i.e., winter, spring, summer, and autumn.

2. Literature Review

2.1 Electric Vehicle (EV) Usage Pattern

The analysis and mining of the EV usage patterns can yield valuable information on the trip and charging characteristics of EVs, which is pivotal for charging infrastructure planning and operation.

Researchers used the survey data or trajectory data of ICEVs to simulate and infer EV usage patterns due to the lack of real EV operational data in the early years when the EV market share was low. For instance, Pearre et al. (2011) extrapolated that even an electric vehicle with a 100-mile range could meet the travel demands of around 30% of users without exerting too much pressure on the grid based on the assumption that users' driving patterns would remain after switching to EVs through analysis of one-year driving data from 484 conventionally fueled vehicles. Tamor et al. (2013) found that EV usage patterns of any individual user diverged from those of the entire group and inferred that the best EV range should between 150 and 200 miles where the equilibrium between cost and energy consumption can be achieved based on the simulation and analysis of real-world operating data from 133 instrumented vehicles within one year.

As EVs are becoming increasingly commonplace, it is more realistic to analyze usage patterns via operation data from real EVs. Weldon et al. (2016) indicated that the EV usage characteristics differed distinctly between the weekends and weekdays, and private EV users tended to take short trips and charge frequently and irregularly through an analysis of three-year driving data from 15 EVs with an identical model in Ireland. Zhang et al. (2019) analyzed 16 usage characteristics including distance travelled, energy consumption per unit and other parameters to reveal users' travel and charging patterns. They hypothesized that the use of air conditioners was responsible for the difference in energy efficiency by using a dataset containing 41 private EVs in Beijing. In contrast to previous studies that used small datasets for analysis, Cui et al. (2022) used a massively large GPS dataset comprising 26,606 EVs to explore the EV usage patterns, which dramatically reduced the bias and instability of the results. Similarly, Sun et al. (2021) also used trajectory big data containing 76,774 EVs in Beijing for one month to explore the travel and charging patterns of EVs. The empirical findings were expected to be helpful for urban planners, city grids and other stakeholders. Yang et al. (2022) used the same dataset to characterize the travel patterns of private EV users. The results indicated that most EV users not only had regular travel and activity patterns, but also had specific preferences for certain locations.

Besides, attempts have been made to investigate the impacts of weather and driving patterns on the energy consumption and usage patterns of EVs. Fetene et al. (2017) found that the energy consumption of EVs increased around 34% and the travel range declined about 25% in winter compared to those in summer, and the seasonal effects were specifically underlined in addition to driving speed, precipitation, etc. Hao et al. (2020) conducted a pioneering investigation into the effects of seasonal changes on the energy consumption and driving range of EVs. More specifically, the operating data of 197 EVs with three use types (i.e., private, taxi and ridesharing) were examined. They found that more intense demands for driving and charging raised in shared and taxi modes of EVs while private EVs consumed significantly more energy in summer and winter. In addition, they stressed that EVs' driving range dropped by over 20% in winter regardless of use types.

2.2 Electric Vehicle (EV) Charging Infrastructure Deployment

It is pivotal to deploy charging infrastructure properly as it can facilitate the adoption of EVs. Up to the present, a variety of charging facilities with different locating methods (e.g., node-based and link-based) have been developed: see some of the recent review work by Deb et al. (2018), Funke et al. (2019), Pagany et al. (2019), Majhi et al. (2021) and Metais et al. (2022). Next, we will review some typical facility location models that have been developed to deploy three typical types of charging facility, namely charging station/post, battery swap station and dynamic wireless charging lane.

Since the charging station is the most traditional and common type of charging infrastructure, it has been the most extensively studied in terms of how to deploy it. Wang and Lin (2009) applied the Set Covering Location Model (SCLM) which is one of the node-based location-allocation models to explore the optimal charging stations deployment locations with the objective of minimizing the number of facilities while meeting all charging demands. Zhang et al. (2015) improved the SCLM where the charging queuing was considered and optimized by tuning the number of chargers in stations and then the model was applied to address the deployment of fast charging stations at highway intersections in California. Frade et al. (2011) and Ko et al. (2017) both used another node-based approach, the Maximum Covering Location Model (MCLM), to situate a given number of charging stations among candidate construction locations and maximize service coverage simultaneously. Zhu et al. (2017) not only regarded the cost of the distance from users to charging stations, but also the queuing time and grid security in the modified p-median model. Furthermore, Janjić et al. (2021) integrated the Analytic Hierarchy Process (AHP) approach into the p-median model, particularly considering the access to parking and power capacity, so as to optimize the number and locations of EV charging stations. In addition to the node-based approaches above, link-based methods have also been abundantly applied in the placements of charging stations. He et al. (2018) exploited the Flow-Capturing Location Model (FCLM) with the consideration of the driving range of EVs to maximize the amount of path flow that could be captured by charging stations to be deployed. Saadati et al. (2022) used the Flow-Refueling Location Model (FRLM) that considered the uncertainty of renewable energy resources, driving range, and capacity constraints, in order to minimize the cost of building charging stations while maximizing the captured traffic flow.

The battery swap station (BSS) with superior operational efficiency and a lower burden on the grid is another charging facility that has drawn widespread attention from scholars. Liu et al. (2016) developed a bi-level optimal programming model where the objective of the upper model was to maximize the net profit of BSSs while the lower model was to minimize the operating costs to resolve the siting and sizing of BSSs in a network. Yang et al. (2021) refined the SCLM based on a data-driven approach to optimizing the locations, size and operational scheduling of such BSSs that provided exclusive vehicles transporting batteries between BSSs and demand points. Wang et al. (2022) developed a bi-objective model and sought the Pareto-optimal solution with the minimum total cost of building BSSs and the maximum operational efficiency of electric freight vehicles via the genetic algorithm and the analysis of GPS trajectory data. Besides, Ding et al. (2021) developed a link-based model to capture demand, aimed to minimize the construction and user travel costs, in order to find the optimal BSS locations for an autonomous fleet. An et al. (2020) refined the construction and operating costs of BSSs (e.g., chargers, battery switching robots, etc.) in their model and particularly factored traffic and weather conditions into the demand forecasts for electric buses, as well as the validity of the model was verified by adopting it into a real network in Australia.

Even though there are still some hurdles to large-scale applications of dynamic wireless charging technology for EVs, it is still regarded as a promising and potential alternative to traditional plug-in charging mode (Panchal et al., 2018). As a result, some academics have been prompted to propel research on how to deploy dynamic wireless charging lanes (DWCLs) rationally. Yan et al. (2017) identified charging demand points and candidate facility locations based on large-scale public transport vehicle mobility data and then derived optimal deployment locations using a node-based model where the objective was to minimize total deployment costs. Similarly, Hwang et al. (2017) optimized the deployment of DWCLs for urban electric buses by developing a mixed integer programming model to minimize construction costs; while it is worth noting that they addressed the issue of multiple routes and on-board battery capacity for buses. Moreover, Mubarak et al. (2021) proposed a novel model where user equilibrium-based traffic flows were regarded as static demand, in order to determine the locations and power of DWCLs while minimizing the investment cost. Tran et al. (2022) aimed to maximize the system performance with considerations of the traffic dynamic and congestion by introducing a link-based mixed-integer linear model to allocate DWCLs. Majhi et al. (2022) developed a non-linear location optimization model based on the FCLM and FRLM, so as to deploy DWCLs with minimum construction and user costs.

2.3 Research Gaps and Aims

As reviewed above, both survey data and emerging big data have been used to characterize travel and charging behaviors of EV users. However, it remains unclear how EV users' behaviors may vary across seasons due to the effects of temperature and weather on battery performance and EV usage patterns. On the other hand, various charging facility location models have been developed to deploy different types of charging facilities, including charging stations/posts, battery swap stations and wireless charging lanes. However, these studies usually ignored the potential influence of seasonal variance in EV charging demand on charging infrastructure deployment. To overcome the two limitations above, we first provide the seasonal variance in charging demand using a unique GPS trajectory dataset which contains 2,658 private EVs in Beijing. The dataset was collected in January, April, July, and October 2018, which were representative months in winter, spring, summer, and autumn. Then, we further explore whether and (if yes) how using different charging demands from the four seasons would influence the subsequent charging infrastructure deployment. The results are expected to be useful for infrastructure planning and investment.

3. Data and Methods

3.1 Study Area: Beijing, China

As the capital of China, Beijing is constituted of 16 districts with 21.89 million inhabitants (BMBS, 2021). Transportation electrification has been greatly and continuously promoted by the government with a diversity of incentive policies in Beijing. By the end of 2020, there had been 411,633 new fuel vehicles (NFVs) (nearly all of which are EVs) in Beijing with an increment of 26.7% in comparison with that in 2019 (BTI, 2021). Meanwhile, charging facilities such as public charging stations have also been deployed widely, and the numbers of public charging stations and posts were around 2,750 and 29,000 at the end of 2020, respectively (EVCIPA, 2021).

3.2 Datasets

In this study, we used a GPS trajectory dataset containing 2,658 private EVs in Beijing. The dataset was collected in January, April, July, and October 2018, which were representative months of winter, spring, summer, and autumn in Beijing. For privacy concerns, the dataset does not contain any sociodemographic information of EV users. Its key fields include vehicle ID, timestamp, latitude, longitude, distance travelled, instantaneous speed, and state of charge (SOC). We extracted travel, parking, and charging patterns using the EV trajectory data analytical framework proposed by Sun et al. (2021) and Yang et al. (2022), so as to explore the seasonal variance in EV charging demand and further its impacts on charging infrastructure deployment. Fig. 1 shows the private EV trajectory dataset and analytical framework.

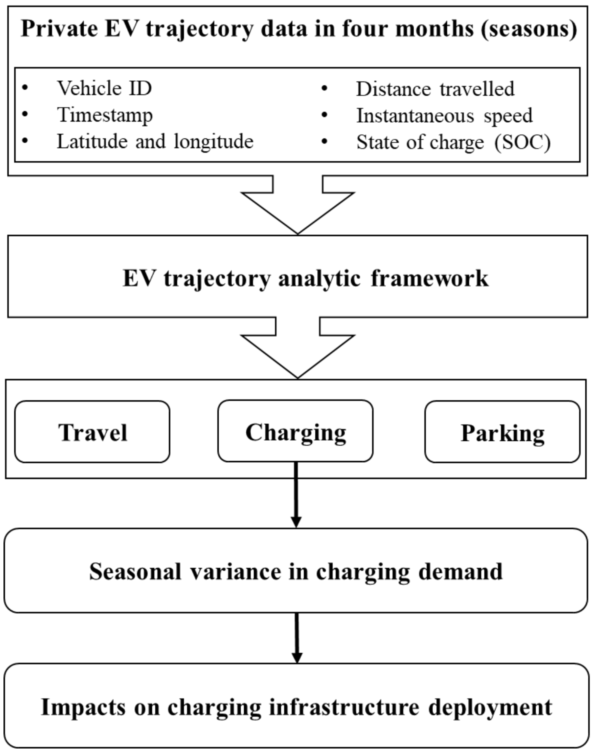
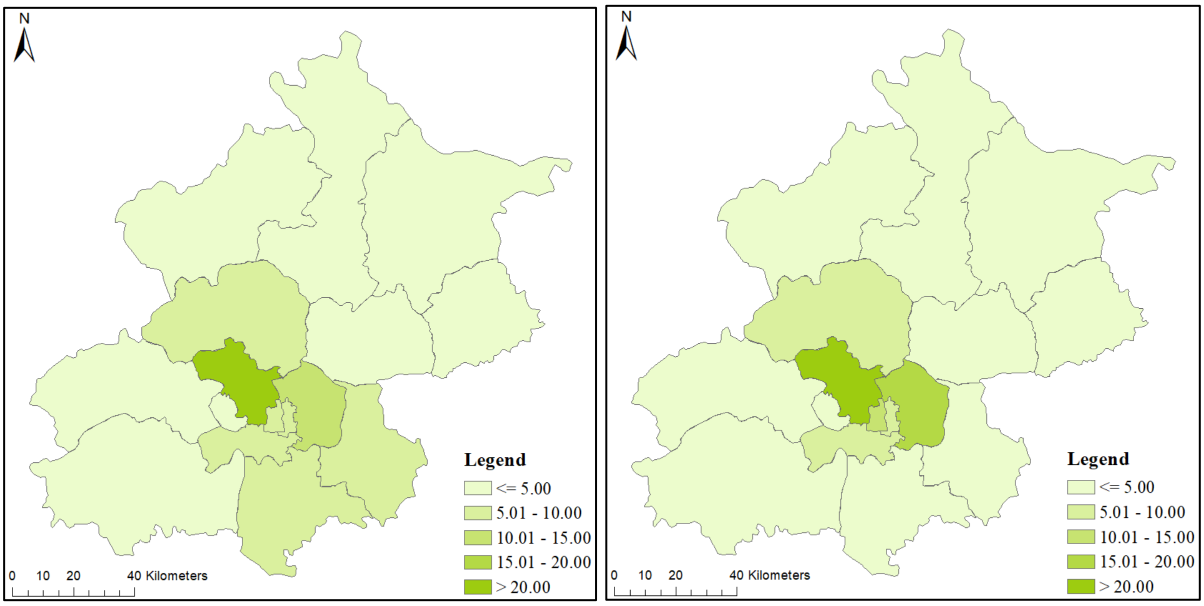


Fig. 1 Private EV trajectory dataset and analytic framework

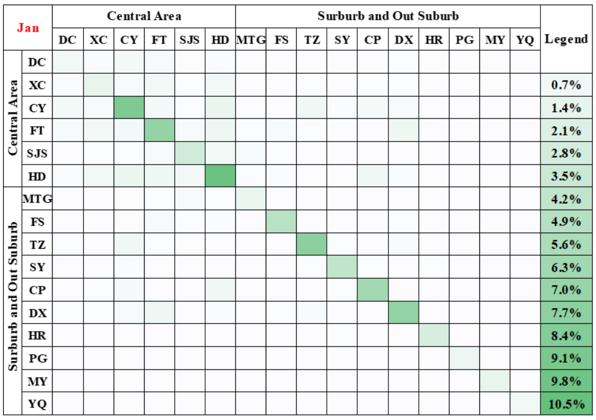
To examine the representativeness of 2,658 private EVs used in this study, Fig. 2 compares the spatial distribution of these 2,658 EV users based on their residential locations against that of over 160,000 private NFVs in Beijing (i.e., the full sample) in 2018. It can be found that these two spatial distributions have similar patterns. Specifically, those districts in the central area of Beijing tended to have a higher percentage of private NFVs. For example, the district Haidian owned more than 20% of private NFVs, as shown in both subfigures. The comparison shows that the sampled data (i.e., the trajectory data of 2,658 private EVs) used in study should be representative in terms of the ownership of private NFVs at the district level.



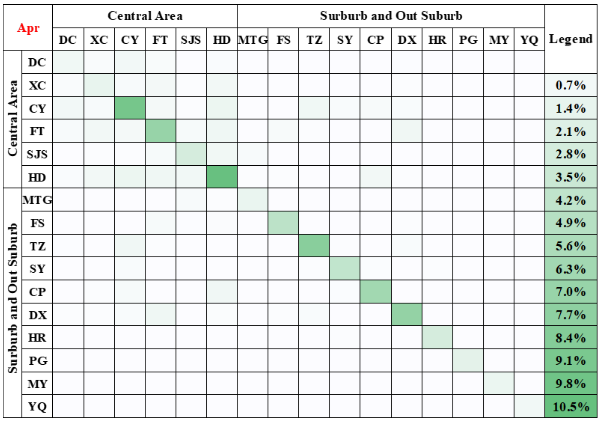
(a) Our sample (b) Full sample

Fig. 2 The percentage of private NFVs by district (which is equal to the ratio of the number of private NFVs in one district to the total number of private NFVs in Beijing)

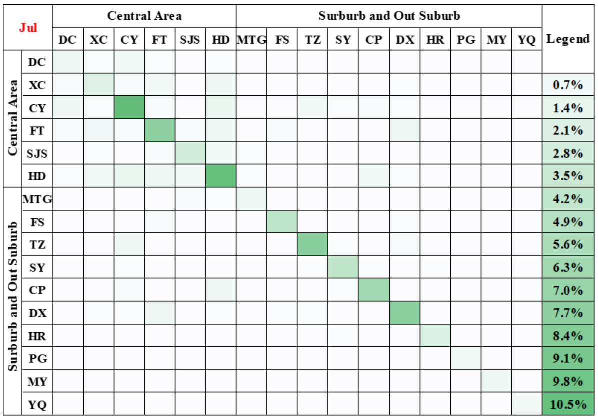
Fig. 3 shows the travel flow patterns at the district level in Beijing in four months (or seasons). In terms of all the sub-figures, each cell represents the ratio of the number of trips between these two districts to the overall number of trips, and cells with darker green imply a larger ratio of trips to the total. Generally, it can be found that most trips occurred within a single district (with the trip origin and destination in the same district) for all four seasons. This indicated that these EV users might have a relatively short trip distance and duration. In comparison to the suburbs and outer suburbs, both intra-district trips and inter-district trips in central areas occurred much more frequently. To show the patterns of inter-district trips clearly, we deliberately removed the intra-district trips from Fig. 3: see the resulting figures in Appendix A in the Supplementary Materials.



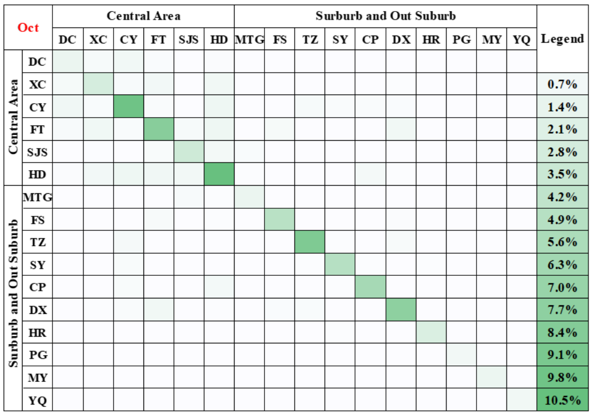
(a) January (or Winter)



(b) April (or Spring)



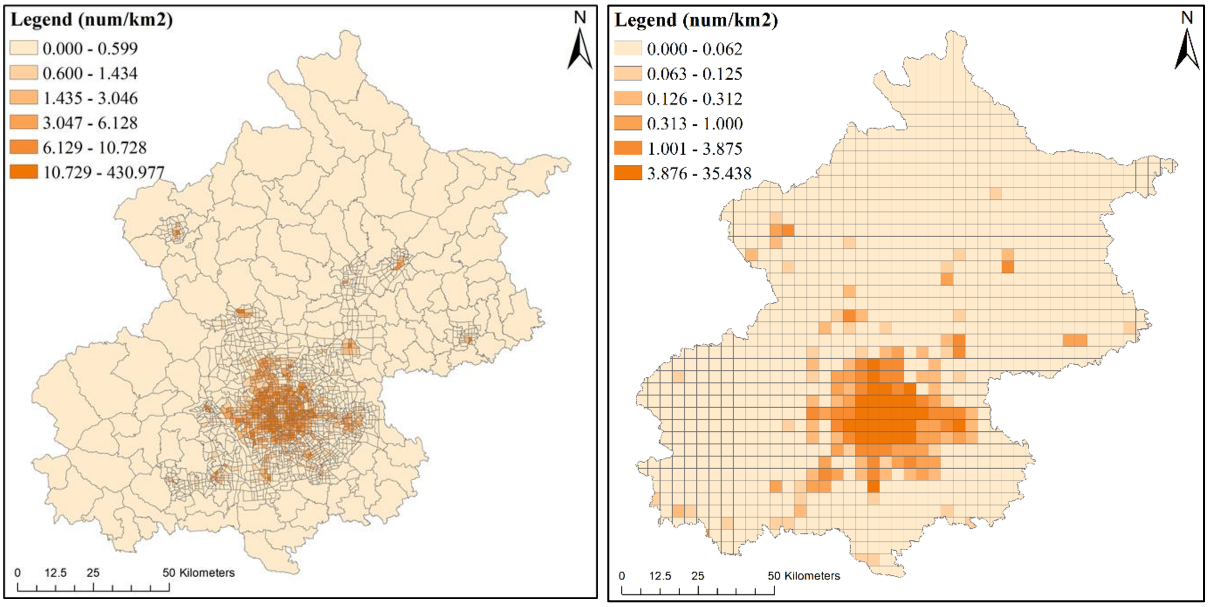
(c) July (or Summer)



(d) October (or Autumn)

Fig. 3 Trip flow patterns at the district level (DC: Dongcheng; XC: Xicheng; CY: Chaoyang; FT: Fengtai; SJS: Shijingshan; HD: Haidian; MTG: Mentougou; FS: Fangshan; TZ: Tongzhou; SY: Shunyi; CP: Changping; DX: Daxing; HR: Huairou; PG: Pinggu; MY: Miyun; YQ: Yanqing)

In addition, we collected the locations of 5,881 public parking lots in Beijing, as charging facilities are most installed at parking lots. Fig. 4 shows the spatial distributions of public parking lots in Beijing at different spatial resolutions (i.e., traffic analysis zone (TAZ) and 4×4 km grid), respectively. It could be found that the so-called modifiable areal unit problem (MAUP), which could lead to statistical variance using different scales for aggregation in spatial analysis, could to some extent influence spatial patterns of public parking lots; while the central area of Beijing tended to have more public parking lots than other areas at both spatial resolutions.



(a) Traffic analysis zone (TAZ) (b) 4×4 km grid

Fig. 4 Spatial distributions of public parking lots in Beijing at different spatial resolutions

3.3 Methodology

3.3.1 P-median Model

As reviewed in Section 2.2, various models have been developed for locating charging facilities, and the p-median model is one of the most-used charging facility location models. Furthermore, EVs get recharged when they are parked at trip destination, in general (Zhuge et al., 2019). This means EV charging demand can be viewed as a series of points distributed across space. P-median model is a typical node-based facility location model and thus is particularly suitable for processing such node-based charging demand. Therefore, we will use the p-median model to explore how seasonal variance in EV charging demand may influence infrastructure deployment. The p-median model aims to determine the locations of p facilities among candidate locations in order to minimize the transportation costs or weighted distances between customers and facilities, ensuring that each customer is serviced by a facility, which can be illustrated mathematically by Equations (1)-(5). Equation (1) represents that the goal is to obtain the minimum sum of distances from the locations of all charging events to their closest charging stations; Equation (2) ensures that only the charging station to be constructed can serve charging demand nearby; Equation (3) indicates that each demand point can only be fulfilled by one charging station; Equation (4) states that the total number of charging stations to be deployed should be p. Equation (5) indicates two binary decision variables.

$$\min \sum_{i \in I} \sum_{j \in J} d_{ij} y_{ij} \tag{1}$$

s.t.

$$y_{ij} \leqslant x_j, i \in I, j \in J \tag{2}$$

$$\sum_{j \in J} y_{ij} = 1, i \in I \tag{3}$$

$$\sum_{j \in J} x_j = p \tag{4}$$

$$x_i, y_{ij} \in \{0,1\}, i \in I, j \in J \tag{5}$$

Where, I is a set of all charging demand points and J is a set of all candidate charging stations (i.e., public parking lots); i and j are a specific charging demand point and a candidate charging station, respectively; d_{ij} indicates the distance from the location of station j to charging demand point i; x_j and y_{ij} are two binary decision variables indicating whether j is selected to deploy a charging station and whether the charging demand i is served by the deployed charging station, respectively; p is the target number of charging stations to be deployed.

After obtaining the layout of charging stations with the p-median model, we further determine the number of charging posts for each station by type. Here, we consider both alternating current (AC) and direct current (DC) charging posts. Specifically, the number of charging posts in a specific station is largely determined by its charging demand and thus can be set to be proportional to the number of charging events that the station has. Further, we choose charger type for each station according to the DC/AC ratios (i.e., the ratio of the number of DC charging posts to the number of AC charging posts) in the current layout of charging facilities in Beijing (see Appendix B in the Supplementary Materials), depending on the station location, as the DC/AC ratio may vary across stations.

3.3.2 Genetic Algorithm (GA)

We will use GA to search for model solutions. Optimizing facility locations is a sort of NP hard problem. GA was initially proposed by JH Holland (1992) to address optimization problems and has been widely applied in a variety of fields (e.g., engineering, economics and management) for solving complex optimization issues, including discrete facility location problems (Basu et al., 2015; Kumar et al., 2014; Michalewicz & Schoenauer, 1996). Furthermore, compared with other algorithms (such as hill climbing algorithm and simulated annealing algorithm), GA has the advantages of easily understandable concept, better global search ability, and more applicable for solving complex and large-scale questions (Lü et al., 2020). A detailed introduction to GA can be found in the cited papers above.

In this study, we set the fitness of GA as the sum of distances from the locations of all charging events to their closest charging stations. Then, we encoded public parking lots (i.e., the candidates for charging stations to be deployed) as genes, which are basic components of chromosomes in GA. The possible values for each gene are 0 or 1. 0 means that no charging station will be deployed at the parking lot, while 1 means that there will be a charging station to be deployed at the parking lot. In terms of the three most important parameters in GA, i.e., the group size of chromosomes, crossover possibility, and mutation possibility, we set them as 20, 0.6, and 0.05, respectively, through trial and error, considering the searching efficiency of GA. Also, we applied a rather strict termination condition for GA. The algorithm will not stop until the ratio R calculated by Equation (6) is smaller than 0.0001 and the termination condition will be checked every 1,000 iterations.

$$R = \frac{F_{i-1000} - F_i}{F_{i-1000}} \quad (6)$$

Where, F_i denotes the fitness of the i_{th} iteration of GA.

4. Results

4.1 Seasonal Effect on Electric Vehicle (EV) Charging Patterns

4.1.1 Seasonal Variance in Statistical Charging Patterns

Table 1 shows the start and end SOCs (i.e., the SOCs with which the EV started and finished charging) in the four months (or seasons), on average. It can be found that private EV users preferred to start charging when the SOC has dropped to around 50% and would finish charging when the SOC has climbed to above 90% regardless of working or non-working days. One exceptional case was that in January (or winter) the start SOC fell to about 43 - 45% which was dramatically smaller than those in the other three months (or seasons). This is likely because of the worse battery performance and more energy consumed by EVs in winter. Besides, instead of the almost identical charging patterns in April (or spring) and October (or autumn), the average start SOC in July (or summer) were slightly lower than those in the other two months (or seasons), remaining at approximately 48% for both working and non-working days. This could be attributed to the more energy consumed through the usage of air conditioners in hot weather (or summer).

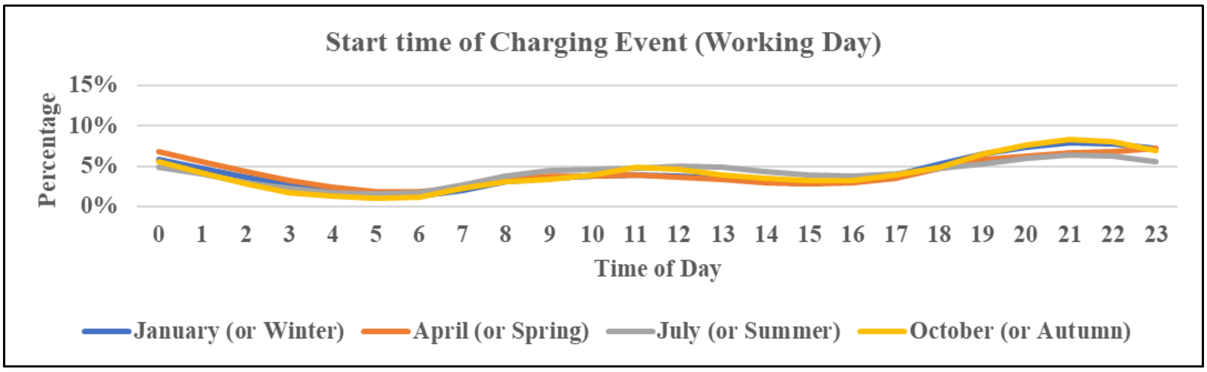
Table 1 EV's average start and end SOCs in different months (or seasons) (unit: %)

Day Type	**SOC Type**	**Month (or Season)**			
		January (Winter)	**April (Spring)**	**July (Summer)**	**October (Autumn)**
Working Day	**Start SOC**	43.50	51.96	48.39	50.86
	End SOC	93.23	94.39	92.91	92.96

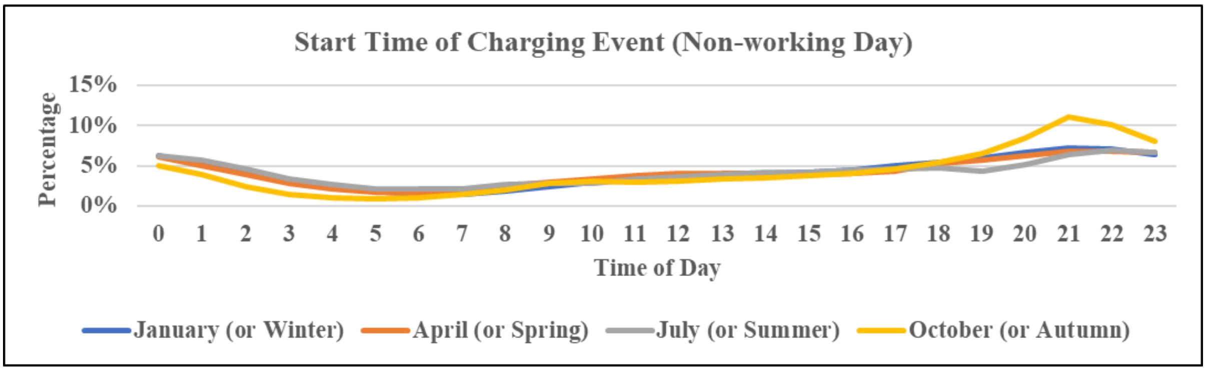
Non-working Day	**Start SOC**	45.73	49.05	48.52	51.47
	End SOC	93.7	93.23	91.71	93.08

4.1.2 Seasonal Variance in Temporal Charging Patterns

Fig. 5 shows the distributions of the start time of charging events in different months (or seasons) on both working and non-working days. Generally, fewer users started charging from 2 am to 6 am regardless of months (or seasons), working or non-working days. However, the situation differed between working and non-working days from 6 am onwards. Specifically, the percentage of charging events fluctuated between 6 am and 5 pm and then continued to rise until around 9 pm on working days; while on non-working days, the upward momentum was maintained from 6 am until around 9 pm. This was likely because EV users utilized their business hours to charge their private EVs on weekdays. Moreover, the peak time for charging was after 6 pm as most users' driving tasks were already completed during the daytime and they could charge their EVs at night or overnight in order to have sufficient charge for the next-day trips. In general, although there existed fluctuations in temporal charging patterns for the four different months (or seasons), similar trends were observed, indicating few seasonal effects on temporal charging patterns.



(a) Working day

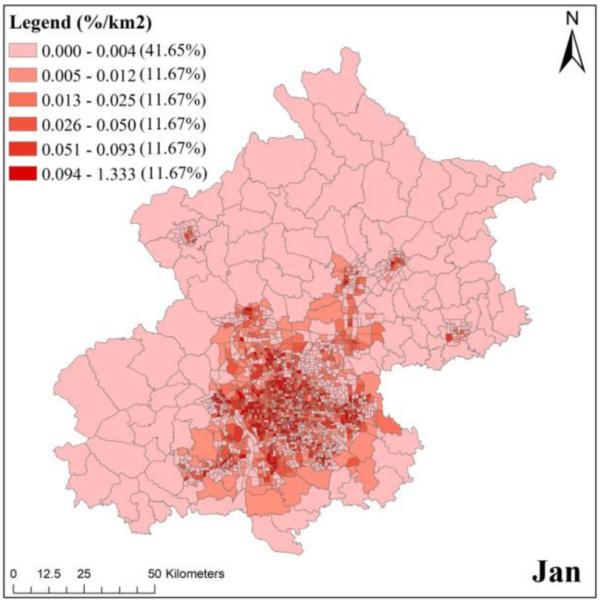


(b) Non-working day

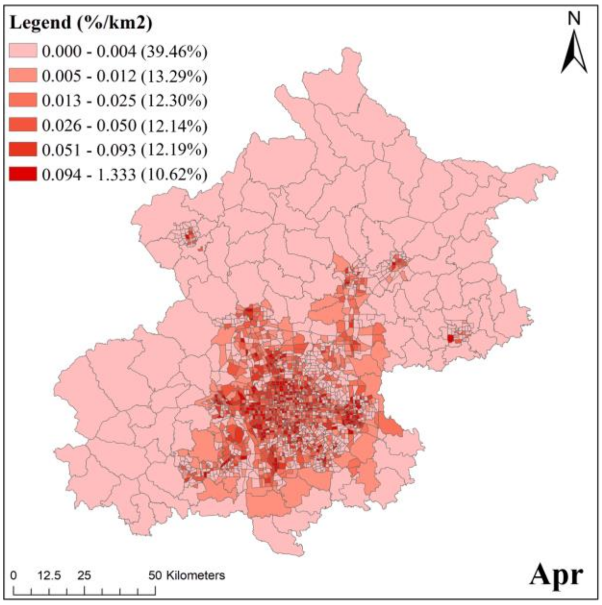
Fig. 5 The distributions of the start time of charging events in different months (or seasons)

4.1.3 Seasonal Variance in Spatial Charging Patterns

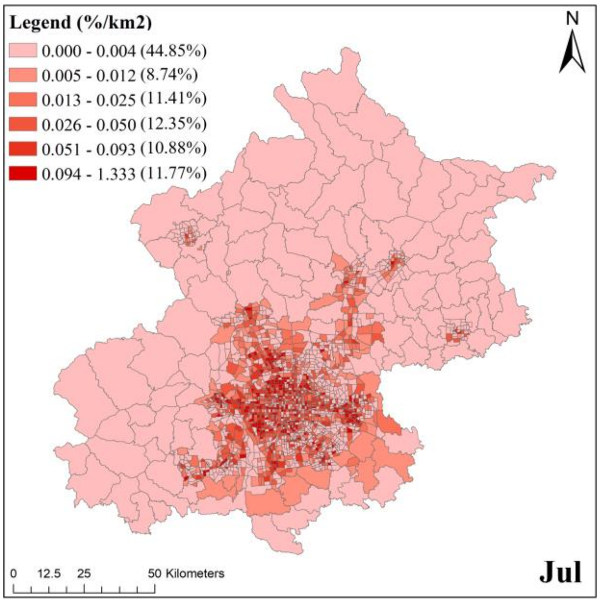
Fig. 6 shows the charging density at the traffic analysis zone (TAZ) level for four different months (or seasons). Here, the charging density in a TAZ was measured as the ratio (of the number of charging events in a TAZ to the total number of charging events within one month) divided by the area of the TAZ. Generally, certain variations in spatial charging patterns across months (or seasons) could be found. For instance, the proportions of TAZs with the charging density between 0.051 %/km^2 and 0.093 %/km^2 varied greatly over the months (or seasons): specifically, they were 11.67%, 12.19%, 10.88%, and 9.84% in winter, spring, summer, and autumn, respectively. However, it could be found that the distinctions in the spatial charging patterns between January (or Winter) and the other months (or seasons) were relatively notable. Specifically, charging events occurred in central areas (including Dongcheng, Xicheng, Chaoyang, Fengtai, Shijingshan, and Haidian) accounted for 46.62% of the total in January (or Winter), whereas the proportions in other months (seasons) were only approximately 44%. These indicated that charging events were denser in central urban areas in winter. This might be because EV users performed most of their daily activities (e.g., work and shopping) in the central areas, and thus they became more frequent to recharge their EVs in these areas. In other words, due to the worse battery performance and increased energy consumption on heating in winter, the EV driving range was limited and therefore the spatial distribution of charging events tended to be compacted. These indicated the seasonal effects on spatial charging patterns of EV users.



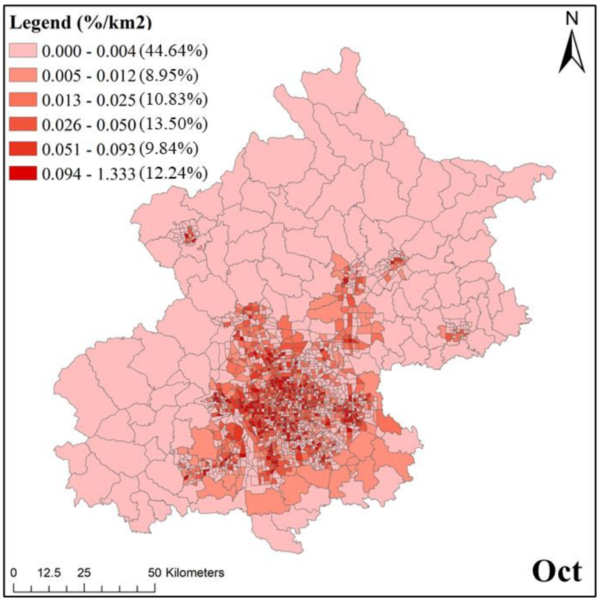
(a) January (or Winter)



(b) April (or Spring)



(c) July (or Summer)



(d) October (or Autumn)

Fig. 6 Spatial distributions of charging events at the TAZ level

Despite the seasonal variance observed in charging patterns of private EVs, the general charging patterns extracted from this study were comparable against those reported by Cui et al. (2022), who used the GPS trajectory data of more than 18,700 private EVs in Beijing (with a sample rate of 11.66%) in 2018. Specifically, from the statistical perspective, we found that the average SOC with which an EV started charging ranged from around 40% to 50%, while Cui et al. (2022) revealed that private EV users preferred to get their EVs recharged when the SOC of an EV dropped to around 30 - 50%, depending on the time of day when an EV was recharged. Also, both our work and the work by Cui et al. (2022) found more private EV users tended to start getting their vehicles recharged at night (i.e., during the period from 7 to 11 PM). The similar charging patterns of private EV users observed in our study and the work by Cui et al. (2022) indicated that our samples (i.e., 2,658 private EVs) should be representative.

4.2 Seasonal Effect on Charging Infrastructure Deployment

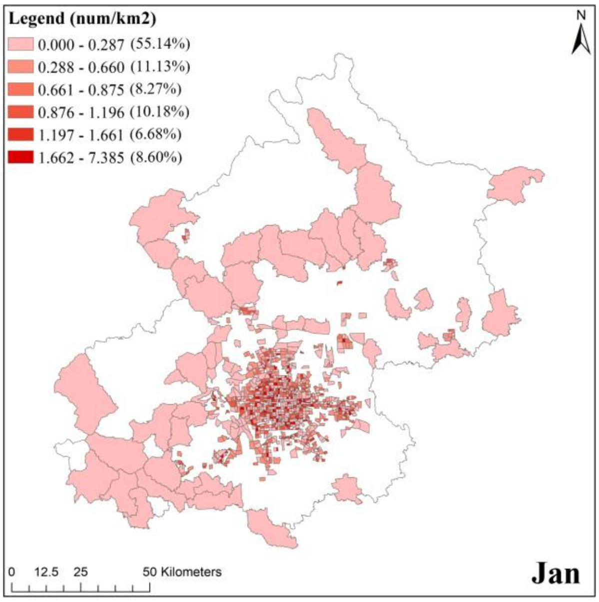
We applied the p-median model to optimize the layout of charging stations based on charging demand of private EVs in different months (or seasons), so as to explore how the seasonal variance in EV charging demand (see Section 4.1) would influence the resulting layout of charging stations/posts at different spatial resolutions (i.e., TAZ and 4×4 km grid). Therefore, we only took the scale of charging facilities in 2017 as a reference when setting up our scenarios, and did not use the existing layout of charging facilities as a base. It is also worth noting that existing charging facilities might have been added with different objectives (e.g., surplus chargers in order for promoting the EV adoption) and constraints (e.g., budget), and thus may not be well optimized. In the baseline scenario (see Section 4.2.1), we set the number of charging stations and posts to be deployed as 621 and 5,640, respectively, which was 30% of the total number of charging facilities in 2017 in Beijing. Since the number of charging facilities to be deployed is an influential factor to the infrastructure deployment, we further explored how varying the number would influence the layout of charging facilities through several "what-if" scenarios (see Section 4.2.2 and 4.2.3).

4.2.1 Deployment of Charging Stations in the Baseline Scenario

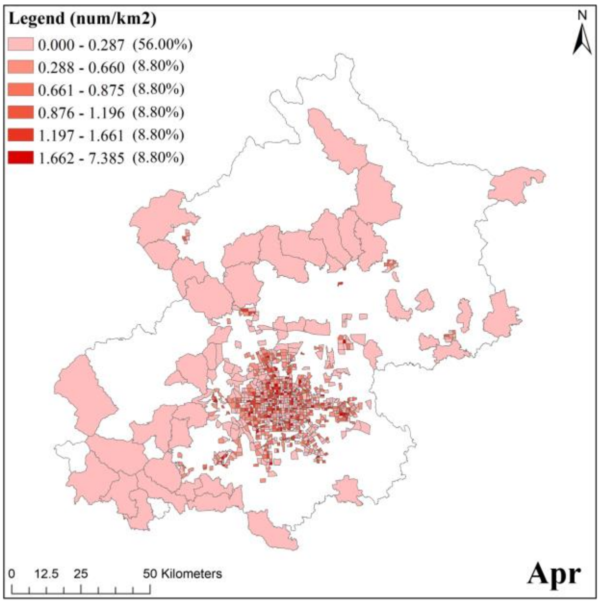
In order to verify the effectiveness of our method (see Section 3.3) in deploying charging infrastructure, we first compared the spatial distributions of the reported charging stations in 2017 against those in the baseline scenario (see Appendix C in the Supplementary Materials). The comparisons show that they have a similar spatial pattern of charging facilities: the central area of Beijing tended to have more charging infrastructure, which to some extent confirms the effectiveness of our method.

Fig. 7 and Fig. 8 show the layouts of charging stations deployed in January, April, July and October (or winter, spring, summer and autumn) at the spatial resolutions of TAZ and 4×4 km grid, respectively, using the indicator of the density of charging stations which is the ratio of the number of charging stations to the land area of the spatial analysis unit (either TAZ or 4×4 km grid). It is worth mentioning that those spatial analysis units devoid of any public parking facilities have been excluded from the visualization, as the method outlined in Section 3.3 assumes the absence of charging infrastructure in such locations. Overall, the central areas tended to have a higher density of charging stations in all the months (or seasons) with different spatial resolutions.

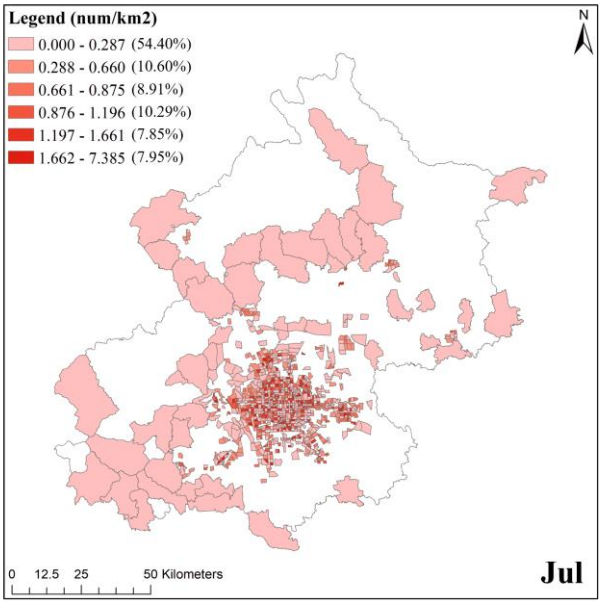
However, seasonal variance did influence the layout of charging stations to some extent. Specifically, according to Fig. 7, even though the proportions of TAZs with a relatively low density of charging station (i.e., lower than 0.287/km^2) in four months (or seasons) were similar, TAZs with the density of charging station between 1.197/km^2 and 1.661/km^2 accounted for 6.68%, 8.80%, 7.85% and 7.95% in winter, spring, summer, and autumn, respectively, showing some degree of seasonal variations. Besides, considering the effects of the modifiable areal unit problem (MAUP), another spatial analysis unit (4×4 km grid) was also applied for exploring the spatial patterns of charging stations to be deployed (see Fig. 8). Similar spatial patterns can be found due to the seasonal variance in charging demand, as evident from those grids with a high density of charging stations (i.e., greater than 0.563/km^2) in four months (or seasons). Despite the fact that the MAUP did influence how much seasonal variation could influence the layout of charging stations to be deployed, seasonal effects could be clearly observed.



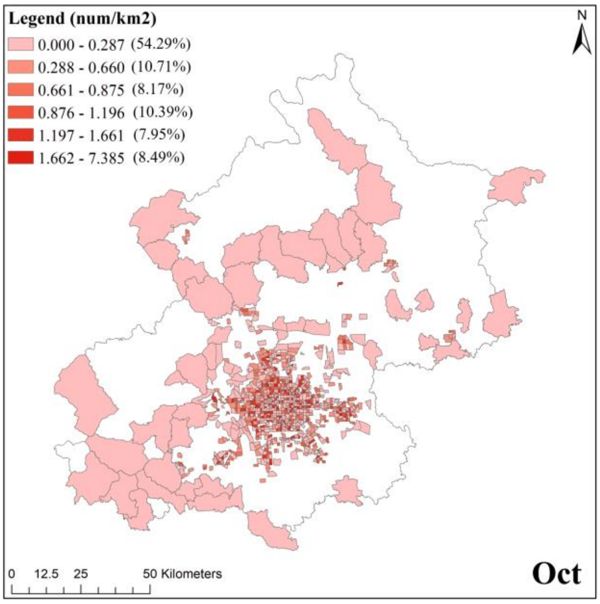
(a) January (or Winter)



(b) April (or Spring)

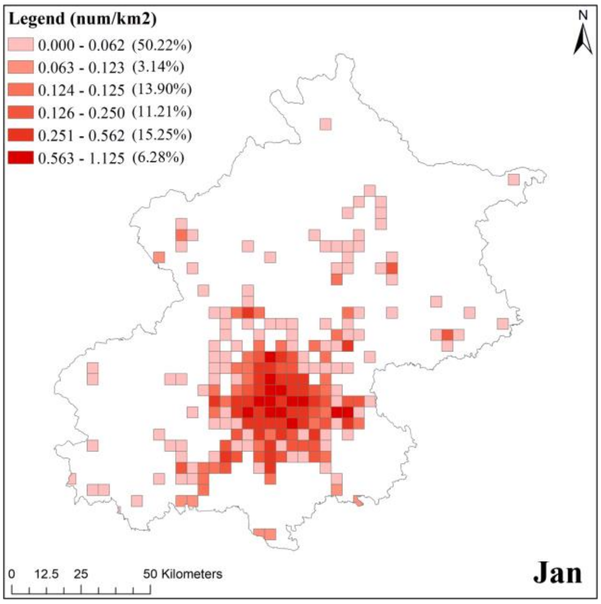


(c) July (or Summer)

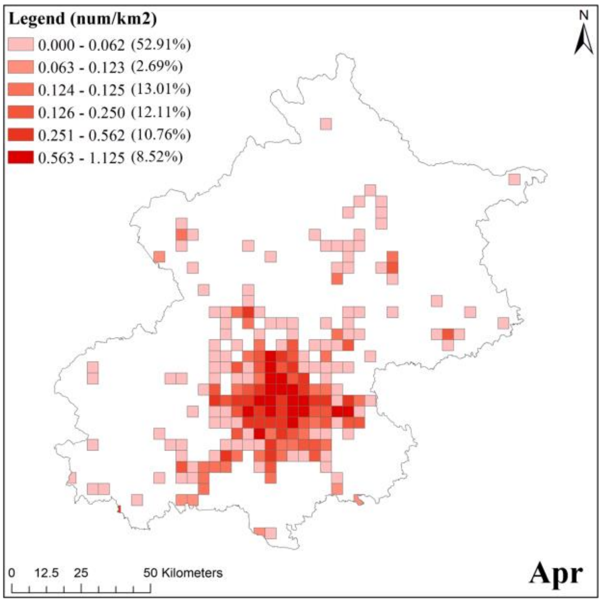


(d) October (or Autumn)

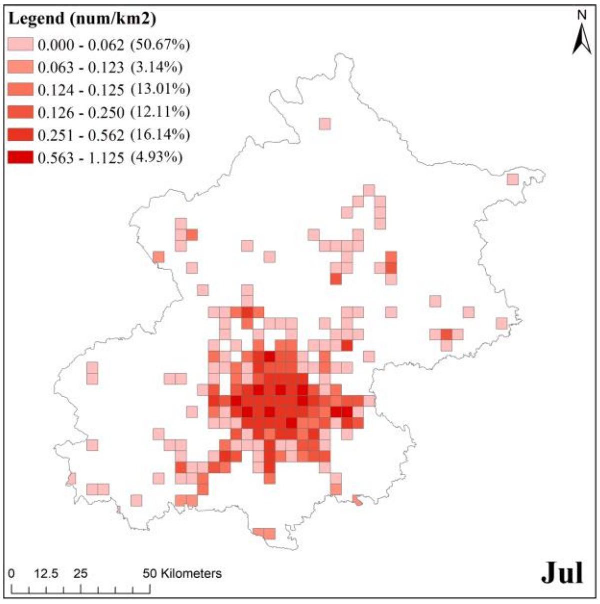
Fig. 7 Spatial distributions of charging stations to be deployed at the TAZ level in the baseline scenario



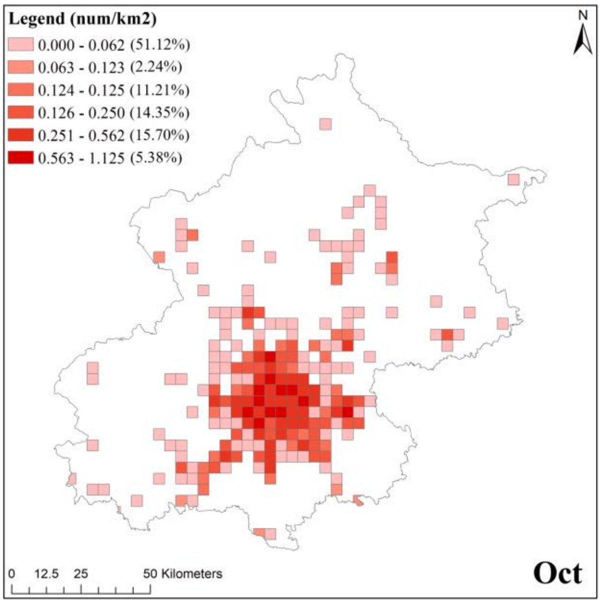
(a) January (or Winter)



(b) April (or Spring)



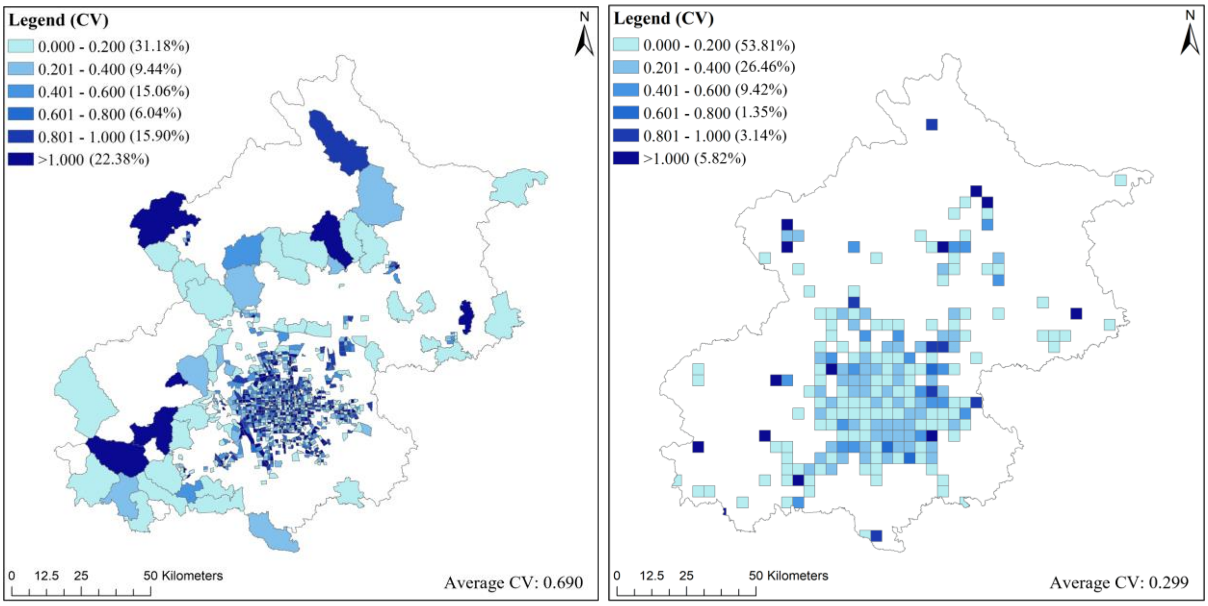
(c) July (or Summer)



(d) October (or Autumn)

Fig. 8 Spatial distributions of charging stations to be deployed at the resolution of 4×4 km grid

Furthermore, the coefficient of variation (CV), which is the ratio of standard deviation to the mean, is utilized to evaluate the degree of variation in the number of charging stations to be deployed in each SAU over different months (or seasons). Fig. 9 shows the spatial distribution of CV at different spatial resolutions (i.e., TAZ and 4×4 km grid): the average CVs were 0.690 at the TAZs level and 0.299 at the 4×4 km grid level, respectively. It could be found that around 22.38% of TAZs with a CV greater than 1.000 were mainly distributed in the central urban areas and a few outer suburbs; while at the 4×4 km grid level, grids with a higher CV (i.e., greater than 1.000) accounted for approximately 5.82% and were principally scattered around outer suburbs. Despite the differences caused by the modifiable areal unit problem (MAUP), we can still find that the spatial analysis units (SAUs) in outer suburbs tended to be greatly influenced by the seasonal variance according to their high CVs, which might be ascribed to fewer facilities and activities in these suburban areas.



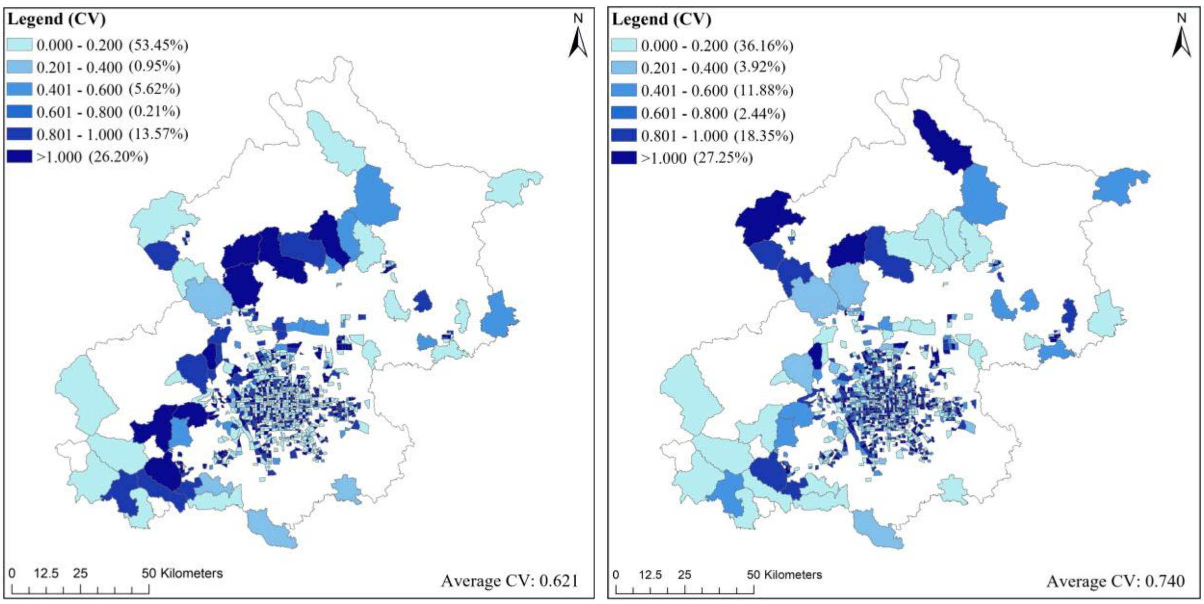
(a) TAZ (b) 4×4 km grid

Fig. 9 Spatial distributions of Coefficient of Variation (CV) for charging stations to be deployed at different spatial resolutions in the baseline scenario

4.2.2 Sensitivity Analysis on the Number of Charging Stations to be Deployed

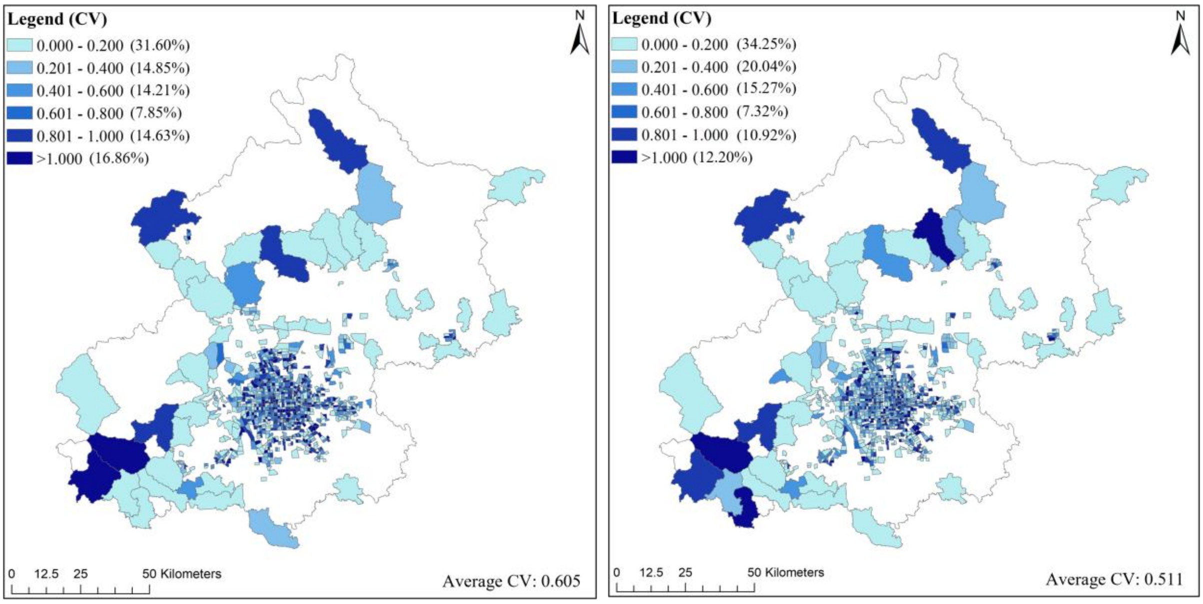
We set up another four “what-if” scenarios to explore how the number of charging stations to be deployed, which is a very influential factor to the outputs of interest, could influence the layouts of charging stations. Specifically, the numbers of charging stations to be deployed were set to 10%, 20%, 40% and 50% of the total number of charging stations in Beijing in the four scenarios, respectively (the baseline uses 30%, and see Appendix D in the Supplementary Materials for the deployments of charging stations in other scenarios). Here, we used spatial distributions of the CV under different SAUs to quantify the extent to which the number of charging stations in each SAU varies across seasons in the four scenarios, as shown in Fig. 10.

Overall, we can still observe the seasonal effect on the layouts of charging stations, as evident from a few TAZs in darker blue (with a CV value above 1.000) in all the four scenarios, indicating the layouts of charging stations in central urban areas and outer suburbs were more sensitive to seasonal variance in charging demand. However, the number of charging facilities to be deployed is a very influential factor and could greatly influence the extent to which the seasonal variance in EV charging demand, and thus could eventually influence the layout of charging facilities. By comparing the average CV and the proportion of TAZs with the CV greater than 1.000 in these scenarios, we could observe more noticeable seasonal effects with fewer charging stations to be deployed. We could draw the similar conclusions with the results from the four scenarios presented under the 4×4 km grid (see Appendix E in the Supplementary Materials).



(a) 10% scenario

(b) 20% scenario

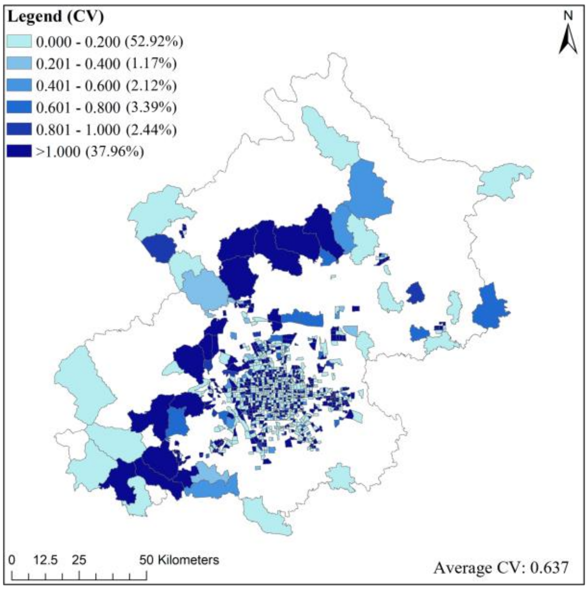


(c) 40% scenario (d) 50% scenario

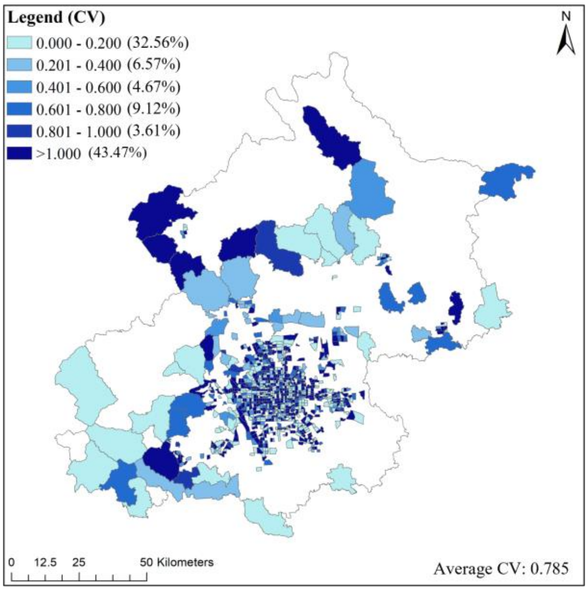
Fig. 10 Spatial distributions of Coefficient of Variation (CV) in the scenarios with different numbers of charging stations to be deployed at the TAZ level

4.2.3 Seasonal Variance in Charging Post Deployment

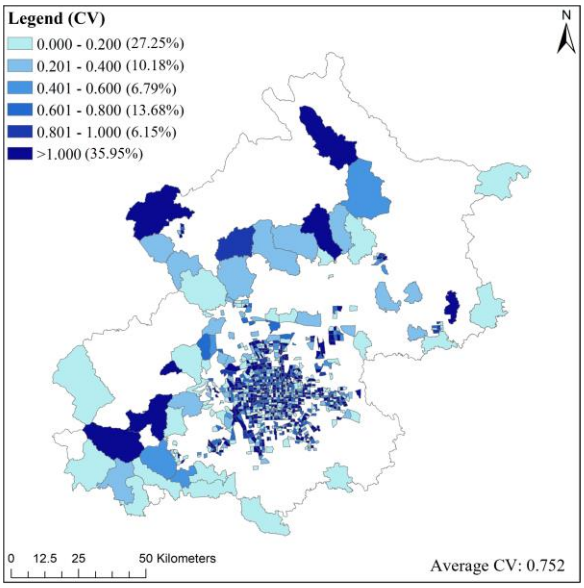
Similar to the above charging station scenarios, another group of "what-if" scenarios were set up to explore how seasonal variance and the number of charging posts to be deployed would affect the facility deployment accordingly. We used the coefficient variation (CV) to quantify the differences as well. As shown by Fig. 11, it could be found that decreasing the number of charging posts to be deployed would result in a comparably high average CV and a higher percentage of TAZs with a higher CV (i.e., greater than 1.000). For instance, the average CV was 0.637 and TAZs with the CV greater than 1.000 accounted for 37.96% in the scenario where 10% of the total number of charging stations were built. These figures were notably higher than those in the 50% scenario. Besides, the spatial distributions of CV for the deployment of charging posts indicated that TAZs with a higher CV were mainly concentred in the central areas and outer suburbs obviously. Hence, it could be found that not only these patterns were consistent with those in the deployments of charging stations, but the seasonal effects on the deployment of charging posts were more distinguishable. Also, we can observe the similar patterns with the spatial distributions of CV at the 4×4 grid level (see Appendix F in the Supplementary Materials). In addition, we demonstrated the spatial distributions of the number of charging posts and the DC/AC ratios in the scenarios where different numbers of charging posts to be deployed (see Appendix G and Appendix H of the Supplementary Materials).



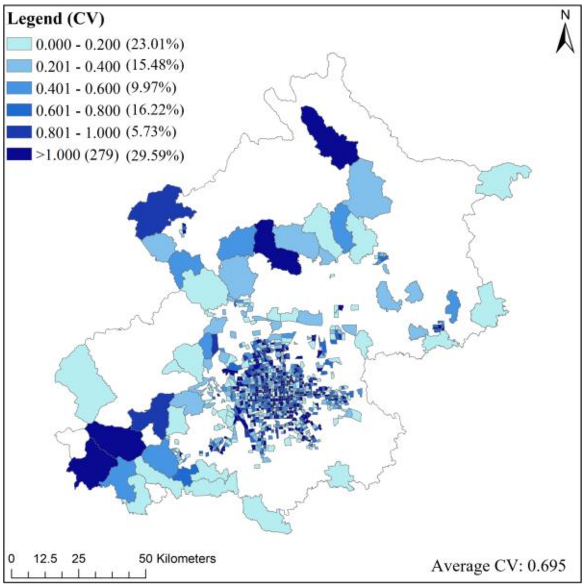
(a) 10% scenario



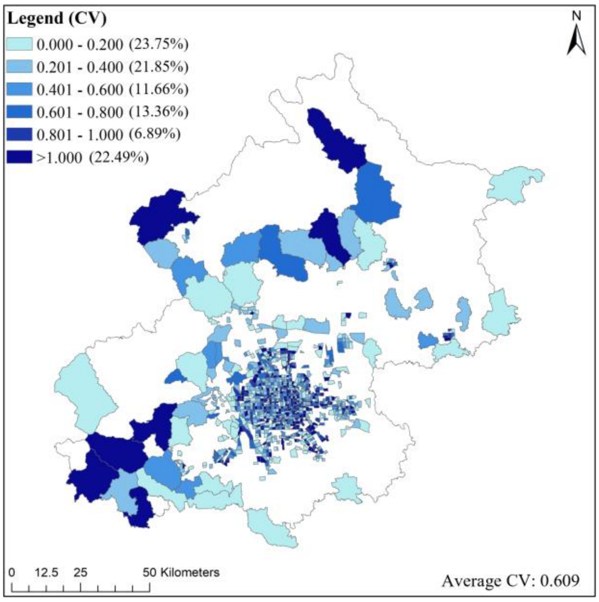
(b) 20% scenario



(c) 30% scenario



(d) 40% scenario



(e) 50% scenario

Fig. 11 Spatial distributions of Coefficient of Variation (CV) in the scenarios with different numbers of charging posts to be deployed at the TAZ level

5. Conclusions

This paper explored seasonal effects on both charging patterns of private EVs and further the layout of charging infrastructure with the consideration of the so-called modifiable areal unit problem (MAUP) using four monthly GPS trajectory datasets collected from 2,658 private EVs in Beijing in four months (or seasons) in 2018.

Empirical findings suggested that charging demands were populated in the central urban area and the demands peaked after 6 pm on both working days and non-working days. Moreover, private EV users tended to get their EVs recharged when the SOC of their EVs dropped to around 50% until it climbed to above 90%. However, seasonal effects on the charging patterns of EV users did exist. In winter, the worse battery performance and heavy heating demand in vehicles could result in higher energy consumption and further higher charging demand in the central area (where EV users tended to perform most of their daily activities, such as work and shopping). Furthermore, the average start SOC of charging events (around 45%) in winter was obviously lower than those in the other seasons (higher than 48%).

When deploying charging facilities with charging demands obtained from different months (or seasons), we found that seasonal variance in charging demand exerts influence on the layouts. We used the Coefficient of Variation (CV) as an indicator to quantify the variance in facility deployment caused by the seasonal variance in charging demand. The spatial distributions of CVs indicated that the layouts of charging facilities in central urban areas and outer suburbs tended to be more sensitive to seasonal variance.

Our findings in this study have several implications for EV-related stakeholders (e.g., the local government, grid operators, and charging infrastructure planners): firstly, despite seasonal variance observed in charging demand of EVs, charging demand across seasons tended to be populated in the central area of Beijing and peaked at night, where and when the load of the local grid was already high caused by residents' daily activities. Therefore, it is of great significance to guide private EV users to charge their vehicles at those areas and during those periods with lower load pressure through direct incentives or smart charging strategies. Then, seasonal variance in charging demand and its further impact on charging infrastructure deployment were observed in this study. In particular, higher energy consumption (and thus lower level of SOC before charging) in winter could aggravate EV users' range anxiety, and thus charging demand in winter should be considered in priority when deploying charging infrastructure. Also, the deployment of charging infrastructure in central urban areas and outer suburbs tended to be more sensitive to the seasonal variance in charging demand. Hence, planners should pay more attention to these areas and fully consider charging demand of EVs across different seasons when determining charging facility locations and capacities.

Our future work will look at the following aspects: firstly, we used four monthly EV trajectory datasets from four different seasons to explore seasonal variance in charging demand. The empirical findings might be improved if a larger dataset with EV trajectories collected throughout a whole year is used. Secondly, we have revealed the seasonal variance of EV charging demand and further its impacts on charging infrastructure deployment in this study. It would be useful to develop a facility location model which could well consider the season variance in deploying EV charging infrastructure.

Acknowledgment

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References

An, K., Jing, W., & Kim, I. (2020). Battery-swapping facility planning for electric buses with local charging systems. International Journal of Sustainable Transportation, 14(7), 489-502.

Basu, S., Sharma, M., & Ghosh, P. S. (2015). Metaheuristic applications on discrete facility location problems: A survey. Opsearch, *52*, 530-561.

BMBS. (2021). 2021 Beijing statistical yearbook. Beijing Municipal Bureau of Statics (BMBS), Beijing, China.

BTI. (2021). 2021 Beijing transport annual report. Beijing Transport Institute (BTI), Beijing, China.

Chen, T., Zhang, X.-P., Wang, J., Li, J., Wu, C., Hu, M., & Bian, H. (2020). A review on electric vehicle charging infrastructure development in the UK. Journal of Modern Power Systems and Clean Energy, 8(2), 193-205.

Cui, D., Wang, Z., Liu, P., Wang, S., Zhang, Z., Dorrell, D. G., & Li, X. (2022). Battery electric vehicle usage pattern analysis driven by massive real-world data. Energy, 250, 123837.

Deb, N., Singh, R., Brooks, R. R., & Bai, K. (2021). A review of extremely fast charging stations for electric vehicles. Energies, 14(22), 7566.

Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018). Review of recent trends in charging infrastructure planning for electric vehicles. Wiley Interdisciplinary Reviews: Energy and Environment, 7(6), e306.

Ding, Z., Tan, W., Lee, W.-J., Pan, X., & Gao, S. (2021). Integrated operation model for autonomous mobility-on-demand fleet and battery swapping station. IEEE Transactions on Industry Applications, 57(6), 5593-5602.

Donkers, A., Yang, D., & Viktorović, M. (2020). Influence of driving style, infrastructure, weather and traffic on electric vehicle performance. Transportation Research Part D: Transport and Environment, 88, 102569.

Doucette, R. T., & McCulloch, M. D. (2011). Modeling the prospects of plug-in hybrid electric vehicles to reduce CO2 emissions. Applied Energy, 88(7), 2315-2323.

EVCIPA (2021). Report on the development of electric vehicle charging infrastructure in China for the years 2020-2021. China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA), Beijing, China.

Fetene, G. M., Kaplan, S., Mabit, S. L., Jensen, A. F., & Prato, C. G. (2017). Harnessing big data for estimating the energy consumption and driving range of electric vehicles. Transportation Research Part D: Transport and Environment, 54, 1-11.

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. P. (2011). Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal. Transportation Research Record, 2252(1), 91-98.

Funke, S. Á., Sprei, F., Gnann, T., & Plötz, P. (2019). How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. Transportation Research Part D: Transport and Environment, 77, 224-242.

GOSC. (2020). New energy vehicle industry development plan (2021-2035). General Office of the State Council (GOSC). Retrieved on 26th October 2022 from http://www.gov.cn/zhengce/content/2020-11/02/content_5556716.htm

Hansen, J., Kharecha, P., Sato, M., Masson-Delmotte, V., Ackerman, F., Beerling, D. J., Hearty, P. J., Hoegh-Guldberg, O., Hsu, S.-L., & Parmesan, C. (2013). Assessing "dangerous climate change": Required reduction of carbon emissions to protect young people, future generations and nature. PloS One, 8(12), e81648.

Hao, X., Wang, H., Lin, Z., & Ouyang, M. (2020). Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles. Journal of Cleaner Production, 249, 119403.

He, J., Yang, H., Tang, T.-Q., & Huang, H.-J. (2018). An optimal charging station location model with the consideration of electric vehicle's driving range. Transportation Research Part C: Emerging Technologies, 86, 641-654.

Holland, J. H. (1992). Genetic algorithms. Scientific American, 267(1), 66-73.

Hwang, I., Jang, Y. J., Ko, Y. D., & Lee, M. S. (2017). System optimization for dynamic wireless charging electric vehicles operating in a multiple-route environment. IEEE Transactions on Intelligent Transportation Systems, 19(6), 1709-1726.

IEA. (2017). Global EV outlook, 2017. Retrieved on 9th August 2022 from https://iea.blob.core.windows.net/assets/8e353b65-961e-4952-9119-9f7ec9d2d682/GlobalEVOutlook2017.pdf

IEA. (2022). Global EV outlook, 2022. Retrieved on 9th August 2022 from https://www.iea.org/data-and-statistics/data-product/global-ev-outlook-2022

Janjić, A., Velimirović, L., Velimirović, J., & Vranić, P. (2021). Estimating the optimal number and locations of electric vehicle charging stations: The application of multi-criteria p-median methodology. Transportation Planning and Technology, 44(8), 827-842.

Järv, O., Ahas, R., & Witlox, F. (2014). Understanding monthly variability in human activity spaces: A twelve-month study using mobile phone call detail records. Transportation Research Part C: Emerging Technologies, 38, 122-135.

Jin, L., He, H., Cui, H., Lutsey, N., Wu, C., Chu, Y., Zhu, J., Xiong, Y., & Liu, X. (2021). Driving a green future: A retrospective review of china's electric vehicle development and outlook for the future. Retrieved on 16th October 2022 from https://trid.trb.org/view/1764439

Johnson, T. V. (2010). Review of CO_2 emissions and technologies in the road transportation sector. SAE International Journal of Engines, 3(1), 1079-1098.

Klingel, J., & von Loesecke, E. (2022). Transportation electrification gets a boost in the infrastructure investment and jobs act. Wiley Online Library, 38(12), 16-19.

Ko, J., Kim, D., Nam, D., & Lee, T. (2017). Determining locations of charging stations for electric taxis using taxi operation data. Transportation Planning and Technology, 40(4), 420-433.

Koncar, I., & Bayram, I. S. (2021). A probabilistic methodology to quantify the impacts of cold weather on electric vehicle demand: A case study in the UK. IEEE Access, 9, 88205-88216.

Kumar, V., Chhabra, J. K., & Kumar, D. (2014). Parameter adaptive harmony search algorithm for unimodal and multimodal optimization problems. Journal of Computational Science, 5(2), 144-155.

Lee, C. T., Hashim, H., Ho, C. S., Van Fan, Y., & Klemeš, J. J. (2017). Sustaining the low-carbon emission development in Asia and beyond: Sustainable energy, water, transportation and low-carbon emission technology. Journal of Cleaner Production, 146, 1-13.

Li, Z., Khajepour, A., & Song, J. (2019). A comprehensive review of the key technologies for pure electric vehicles. Energy, 182, 824-839.

Liu, W., Niu, S., Xu, H., & Li, X. (2016). A new method to plan the capacity and location of battery swapping station for electric vehicle considering demand side management. Sustainability, 8(6), 557.

Lü, X., Wu, Y., Lian, J., Zhang, Y., Chen, C., Wang, P., & Meng, L. (2020). Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm. Energy Conversion and Management, 205, 112474.

Majhi, R. C., Ranjitkar, P., & Sheng, M. (2022). Optimal allocation of dynamic wireless charging facility for electric vehicles. Transportation Research Part D: Transport and Environment, 111, 103461.

Majhi, R. C., Ranjitkar, P., Sheng, M., Covic, G. A., & Wilson, D. J. (2021). A systematic review of charging infrastructure location problem for electric vehicles. Transport reviews, 41(4), 432-455.

Metais, M.-O., Jouini, O., Perez, Y., Berrada, J., & Suomalainen, E. (2022). To much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options. Renewable and Sustainable Energy Reviews, 153, 111719.

Michalewicz, Z., & Schoenauer, M. (1996). Evolutionary algorithms for constrained parameter optimization problems. Evolutionary Computation, 4(1), 1-32.

Nicholas, M. (2019). Estimating electric vehicle charging infrastructure costs across major US metropolitan areas. Retrieved on 17th September 2022 from https://theicct. org/sites/default/files/publications/ICCT_EV_Charging_Cost_20190813. pdf

Mubarak, M., Üster, H., Abdelghany, K., & Khodayar, M. (2021). Strategic network design and analysis for in-motion wireless charging of electric vehicles. Transportation Research Part E: Logistics and Transportation Review, 145, 102179.

OLEV. (2013). Driving the future today: A strategy for ultra low emission vehicles in the UK. Office for Low Emission Vehicles (OLEV), London, UK. Retrieved on 6th September 2022 from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/239317/ultra-low-emission-vehicle-strategy.pdfo

Pagany, R., Ramirez Camargo, L., & Dorner, W. (2019). A review of spatial localization methodologies for the electric vehicle charging infrastructure. International Journal of Sustainable Transportation, 13(6), 433-449.

Panchal, C., Stegen, S., & Lu, J. (2018). Review of static and dynamic wireless electric vehicle charging system. Engineering Science and Technology, an International Journal, 21(5), 922-937.

Pearre, N. S., Kempton, W., Guensler, R. L., & Elango, V. V. (2011). Electric vehicles: How much range is required for a day's driving? Transportation Research Part C: Emerging Technologies, 19(6), 1171-1184.

Saadati, R., Saebi, J., & Jafari-Nokandi, M. (2022). Effect of uncertainties on siting and sizing of charging stations and renewable energy resources: A modified capacitated flow-refueling location model. Sustainable Energy, Grids and Networks, 31, 100759.

Sun, M., Shao, C., Zhuge, C., Wang, P., Yang, X., & Wang, S. (2021). Uncovering travel and charging patterns of private electric vehicles with trajectory data: Evidence and policy implications. Transportation, 1-31.

Tamor, M. A., Gearhart, C., & Soto, C. (2013). A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. Transportation Research Part C: Emerging Technologies, 26, 125-134.

Thomas, C. S. (2009). Transportation options in a carbon-constrained world: Hybrids, plug-in hybrids, biofuels, fuel cell electric vehicles, and battery electric vehicles. International Journal of Hydrogen Energy, 34(23), 9279-9296.

Tran, C. Q., Keyvan-Ekbatani, M., Ngoduy, D., & Watling, D. (2022). Dynamic wireless charging lanes location model in urban networks considering route choices. Transportation Research Part C: Emerging Technologies, 139, 103652.

Wang, S., Shao, C., Zhuge, C., Sun, M., Wang, P., & Yang, X. (2022). Deploying battery swap stations for electric freight vehicles based on trajectory data analysis. IEEE Transactions on Transportation Electrification, 8(3), 3782-3800.

Wang, Y.-W., & Lin, C.-C. (2009). Locating road-vehicle refueling stations. Transportation Research Part E: Logistics and Transportation Review, 45(5), 821-829.

Weldon, P., Morrissey, P., Brady, J., & O'Mahony, M. (2016). An investigation into usage patterns of electric vehicles in Ireland. Transportation Research Part D: Transport and Environment, 43, 207-225.

Yan, L., Shen, H., Zhao, J., Xu, C., Luo, F., & Qiu, C. (2017). CatCharger: Deploying wireless charging lanes in a metropolitan road network through categorization and clustering of vehicle traffic [Paper presentation]. IEEE INFOCOM 2017 - IEEE Conference on Computer Communications, Atlanta, GA, United States.

Yang, X., Shao, C., Zhuge, C., Sun, M., Wang, P., & Wang, S. (2021). Deploying battery swap stations for shared electric vehicles using trajectory data. Transportation Research Part D: Transport and Environment, 97, 102943.

Yang, X., Zhuge, C., Shao, C., Huang, Y., Tang, J. H. C. G., Sun, M., Wang, P., & Wang, S. (2022). Characterizing mobility patterns of private electric vehicle users with trajectory data. Applied Energy, 321, 119417.

Zhang, L., Shaffer, B., Brown, T., & Samuelsen, G. S. (2015). The optimization of DC fast charging deployment in California. Applied Energy, 157, 111-122.

Zhang, X., Zou, Y., Fan, J., & Guo, H. (2019). Usage pattern analysis of Beijing private electric vehicles based on real-world data. Energy, 167, 1074-1085.

Zhu, J., Li, Y., Yang, J., Li, X., Zeng, S., & Chen, Y. (2017). Planning of electric vehicle charging station based on queuing theory. The Journal of Engineering, 2017(13), 1867-1871.

Zhuge, C., Shao, C., & Li, X. (2019). Empirical analysis of parking behaviour of conventional and electric vehicles for parking modelling: A case study of Beijing, China. Energies, 12(16), 3073.