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Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of Beijing, China

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ABSTRACT

In this paper, we present a case study on planning the locations of public electric vehicle (EV) charging stations in Beijing, China. Our objectives are to incorporate the local constraints of supply and demand on public EV charging stations into facility location models and to compare the optimal locations from three different location models. On the supply side, we analyse the institutional and spatial constraints in public charging infrastructure construction to select the potential sites. On the demand side, interviews with stakeholders are conducted and the ranking-type Delphi method is used when estimating the EV demand with aggregate data from municipal statistical yearbooks and the national census. With the estimated EV demand, we compare three classic facility location models – the set covering model, the maximal covering location model, and the *p*-median model – and we aim to provide policy-makers with a comprehensive analysis to better understand the effectiveness of these traditional models for locating EV charging facilities. Our results show that the *p*-median solutions are more effective than the other two models in the sense that the charging stations are closer to the communities with higher EV demand, and, therefore, the majority of EV users have more convenient access to the charging facilities. From the experiments of comparing only the *p*-median and the maximal covering location models, our results suggest that (1) the *p*-median model outperforms the maximal covering location model in terms of satisfying the other's objective, and (2) when the number of charging stations to be built is large, or when minor change is required, the solutions to both models are more stable as *p* increases.

1. Introduction

Promoting the usage of EVs is a long-term solution designed to maintain a healthy balance of urban mobility and energy consumption. As the largest carbon-emitting country in the world, China is putting a great deal of effort into EV marketisation. Central and local governments have both launched many strategies to promote the construction of public charging

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infrastructure. However, because the EV market is still in its infancy and lacks sophisticated planning methods, more research work is needed regarding an appropriate deployment plan for public charging infrastructure (Budde et al., 2012).

Optimal locations for public charging facilities are an important issue in transport planning. EVs are promoted worldwide as an effective mobility alternative to address peak oil and air pollution problems (Liu et al., 2013). However, along with this new technology come challenges (Romm, 2006). Among these factors, limited accessibility to charging facilities has been highlighted as a very pressing problem that largely constrains the popularisation and market acceptance of EVs (Melaina and Bremson, 2008; Wang et al., 2013). For many European and Asia-Pacific regions, where many people live in high-rise apartments, people have to rely more on public charging infrastructure due to limited access to off-street home charging (Giménez et al., 2014). It is estimated that 45% of the charging demand would have to be satisfied by fast public charging stations (Liu, 2012).

The driving factors for charging facility development are highly dependent on the local settings (Mikler, 2009; Wells, 2010). The multiple stakeholders involved and their motivations will affect the constraints and objectives of the facility location models (Kley et al., 2011). Many other studies have suggested that the potential main locations for charging facilities should be the workplace, public shopping malls, and university parking lots (Chen and Liao, 2013; Xi et al., 2013), but these locations may not be the investment foci in many Chinese cities. The present deployment of public charging stations in Beijing is largely a top-down planning process. The government has indicated a number of potential location sites for public charging stations. The unique planning system in Beijing provides an opportunity to improve the facility location decisions by considering contextual factors such as local settings, spatial settings, and government policies. Such local settings can be the driving factors for charging facility development (Mikler, 2009; Wells, 2010).

Unlike many other facility location problems, such as in the application domains of medical services (Dökmeci, 1977; Marianov and ReVelle, 1996; Jia et al., 2007), fire facilities (Badri et al., 1998), humanitarian logistics (Balcik and Beamon, 2008), postal services (Bouliane and Laporte, 1992), school locations (Pizzolato, 1994) and waste management (Barros et al., 1998), in our application, the convenience of access to locations has a direct impact on the consumption (*i.e.*, the adoption of EVs). The more conveniently accessible are the charging stations for potential EV users, the higher is the expected adoption level of EVs. Particularly at the present time, when the government is strongly promoting the use of environmentally sustainable vehicles and planning the supporting infrastructure, the ease of access to EV charging facilities should be a major consideration when determining their locations. This also motivates us to consider the socio-demographic factors, which may impact upon the EV adoption level, in different areas of Beijing, when determining the optimal locations.

This paper has two objectives. The first objective is to study the potential of incorporating institutional and spatial factors into facility location models, such as the local government requirements on charging facility deployment and the spatial distribution of the potential sites across the city. The second objective is to compare the optimal facility locations based on three classic location models and to provide transport planning implications. Regarding the first objective, we will first derive potential demand and supply based on the local institutional and spatial constraints summarised from interviews, policy studies and spatial analysis. Then, regarding the second objective, we will incorporate the supply and demand information into models of three popular facility location problems – the set covering problem (SCP), the maximal covering location problem (MCLP), and the *p*-median problem (PMP) – to conduct a case study of public EV charging stations' planning in Beijing, China. By assessing the effectiveness of these models and examining the characteristics of the solutions, we aim to identify the optimal locations of public EV charging stations.

The rest of the paper is organised as follows. In Section 2, we will review general facility location models and related studies on public EV charging stations. In Section 3, we will describe the study area of Beijing, the methods that we used to estimate the demand and supply of the EV charging stations, and the three models. The socio-economic and demographic indicators of each census tract will be considered in order to estimate the charging demand while the institutional and spatial constraints will influence the supply of public charging stations. We will then present the mathematical formulations of SCP, MCLP and PMP. In Section 4, we will present and compare the results from these three models. In Section 5, we conclude the paper with policy recommendations for the deployment of public EV charging stations in Beijing.

2. Literature review

This research is grounded on classic location science (Church, 1999; Yeh and Chow, 1996; Murray, 2010; Ritsema van Eck and De Jong, 1999). In this section, we will first review the literature on general facility location models and then other recent relevant papers that develop models more specifically for EV charging infrastructure.

2.1. Facility location models

Facility location problems have been studied for more than half a century (for example, Cooper, 1963). As the literature on location problems is vast, here we review only the papers on the fundamental models; for detailed surveys on facility location problems, we refer the reader to Hale and Moberg (2003), ReVelle and Eiselt (2005), ReVelle et al. (2008) and Farahani et al. (2012). SCP is one of the most popular problems for facility location planning. The objective of SCP is to minimise the number of facilities, whereas all the demands of communities have to be covered by an established facility within a specified distance; in the rest of this paper we call this the critical coverage distance or radius. Toregas et al. (1971) considered SCP for emergency facility location problems. In their problem, to ensure a short response time for each community, there should be at least one emergency facility located within the critical coverage distance. Gleason (1975) used SCP to determine bus stop locations. The objective was to locate the minimum number of bus stops so that each passenger did not need to walk more than a specified distance to the nearest bus stop. Batta and Mannur (1990) proposed an extended version of SCP for determining the locations of fire trucks. In their model, multiple fire trucks were required to be within an acceptable standard distance from some communities. Although an optimal solution for the SCP can minimise the number of facilities to be located and ensure that all demand points are covered by at least one facility within the critical coverage distance, SCP is quite restrictive in the sense that it requires all the demand points to be covered by the chosen set of locations. However, in reality there are usually situations where there is no possible location to cover the demand point within the critical coverage distance or where the budget is not sufficient to build all suggested facilities. Therefore, the ideal solution may become impractical. Furthermore, in SCP, each demand point is regarded as equally important because its level of demand is not considered in the model.

MCLP, introduced by Church and ReVelle (1974), addresses the above issues of SCM. Given the number of facilities to be built, denoted by p, MCLP aims to maximise the total level of demand to be covered, within the critical coverage distance, by p facilities. Schilling et al. (1979) presented the problem of locating basic facilities and specialised equipment for a fire protection system in Baltimore City. Daskin (1983) presented the maximal expected covering location problem that takes into account the chance of the server being busy when a call enters the service system. ReVelle and Hogan (1989) introduced a probabilistic version of MCLP which aims to maximise the population that will find a server within a pre-specified limit of time or distance with a probability of at least a certain level. Berman and Krass (2002) introduced the generalised MCLP which allows for partial coverage of demand points. In the generalised MCLP, the level of coverage is a decreasing step function of the distance to the closest established facility. Oztekin et al. (2010) used an enhanced formulation of MCLP with a criticality index analysis metric to track medical assets in a healthcare setting with an RFID infrastructure. Although MCLP has greater problem feasibility over SCP in terms of coverage and budgetary constraints, SCP and MCLP both have shortcomings in that the distances are used only to indicate whether a facility can cover a demand point or not, while the actual magnitude of the distance is not directly incorporated into the model.

PMP, which was introduced by Hakimi (1964), aims to minimise the total demand-weighted distances between facilities and demand points, where the p facilities are to be located. Thus, the p-median model tends to locate facilities more conveniently for the majority of the population they serve. This feature helps to overcome the shortcomings of the SCP and MCLP previously addressed. ReVelle and Swain (1970) proposed an integer linear program to solve the problem. Nicholas et al. (2004) used PMP with geographic information systems to design a hydrogen-refuelling infrastructure in California. Snyder and Daskin (2005) presented the reliability PMP which minimises a weighted sum of the day-to-day transportation cost and the expected failure cost, where each facility has a chance of failing to operate.

In addition to the above traditional models that specify the demands at nodes, facility location models that consider the demands of origin–destination pairs are becoming more popular for determining the locations of refuelling facilities in applications that involve trips. For these models, the demands are associated with the paths of the trips and are called flows. Each refuelling facility can capture the flows of a set of trips and the locations are selected to capture the flows as much as possible, given that p facilities are to be built. Hodgson (1990) proposed the flow-capturing location model (FCLM) as a mathematical formulation for this problem. Kuby and Lim (2005) considered the vehicle range limitations that (i) vehicles may need to refuel multiple times and (ii) the locations of refuelling stations along the path are important whether or not the vehicle can finish the whole trip, and so they developed a flow-refuelling location model (FRLM) to determine the locations of hydrogen stations to refuel vehicles. The model maximises the total flow volume that can be refuelled. Kuby et al. (2009) used the FRLM model to design a robust refuelling infrastructure in Florida at the metropolitan Orlando and statewide scales. Upchurch et al. (2009) presented a capacitated flow-refuelling location model (CFRLM) that limits the number of vehicles that can be refuelled at each alternative-fuel station. They conducted a case study of the Arizona state highway network and found that the optimal locations to the incapacitated FRLM may only be suboptimal to CFRLM.

There is no uniform criterion regarding which model is better than the others because it depends considerably upon how we measure the effectiveness of facility location (Jia et al., 2007). Research has been carried out to compare the effectiveness of different facility location models. Hodgson and Rosing (1992) proposed a hybrid model to examine the trade-off between the FCLM and PMP objectives and they found that the PMP objective suffered more damage from the trade-off than the FCLM objective. Upchurch and Kuby (2010) conducted case studies at the metropolitan scale of Orlando and the statewide scale of Florida to compare PMP and FRLM for locating alternative-fuel stations. They assessed how well the stations that had been located by each model performed on the other's objective, and their results suggested that the stations obtained by FRLM generally performed better. They found that at the metropolitan scale both models produce similar results that tend to disperse the charging facilities over a wide area. However, at the statewide scale the two models suggested very different locations of stations, where PMP disperses the facilities while FRLM builds up connected networks that can cover long-distance flows, and they performed very badly in terms of the other's objective function. In terms of solution stability, locations chosen by FRLM were more stable than those suggested by PMP, especially at the metropolitan scale.

2.2. Application of location models in EV charging facilities

In recent years, due to rapid technological advances in EV, facility location models have been applied to study the location-planning problem of EV charging facilities. The deployment of EV charging facilities shares some similarities with petrol-refuelling stations, such as the consideration of energy demand from car users and site availability. On the other hand, there are a couple of key differences. Firstly, the refuelling petrol vehicles can take place only at petrol stations, whereas EVs can be charged either at home or at public charging facilities (Liu, 2012). Secondly, the spatial distribution of EV charging facilities will also need to consider the local electricity grid system, in which stakeholders in the government-owned utility are involved (Clement-Nyns et al., 2010; Deilami et al., 2011).

The studies of EV charging stations applying location models can be broadly categorised into three types. In the first set of these studies, charging facilities were located where the charging demand was the highest. Kameda and Mukai (2011) used taxi probe data to simulate the traffic at the district level, and it was recommended that the charging stations should be placed in the most frequently visited districts. Liu (2012) proposed a charging facility assignment model based on the regional charging demand, which was estimated by the regional parking spaces and the number of petrol-refuelling stations. Wang et al. (2013) developed a quantitative model for EV charging stations based on the energy consuming equivalence principle and recommended that charging stations be located in areas with relatively higher petrol sales. In these studies, the 'hotspots' of the demand for charging would be served as a priority. This approach can be used to solve the facility location problems at the demonstration stage of EV deployment.

In the second category of studies, the objective of the facility location models was to maximise the service coverage of EV demand. For example, Frade et al. (2011) used MCLP to decide the number of EV charging stations needed. Wang and Wang (2010) used a dual-objective to maximise population coverage while minimising the locating cost of vehicle refuelling stations. Xu et al. (2013) proposed a GIS-based collective user utility maximisation model to determine the number of charging stations needed to match the urban charging demand. Dong et al. (2014) proposed an activity-based assessment method and used GPS-based travel survey data to analyse the impact of deploying charging infrastructure on promoting consumer acceptance of battery electric vehicles. Their objective was to minimise the total number of missed trips. Riemann et al. (2015) presented a problem of determining wireless power transfer facilities for electric vehicles and the objective was to maximise the captured traffic flow.

In the last group of studies that apply to facility location models in EV charging stations, the objective function was to minimise costs in various forms, such as total travel distance (Hanabusa and Horiguchi, 2011), time and budget (Phonrattanasak and Leeprechanon, 2012), and the integrated cost of these three components (Baouche et al., 2014). Chen et al. (2013) developed a parking-based assignment method to determine the public charging facility location that aimed to minimise the EV users' station access costs. Feng et al. (2012) presented a charging station planning model based on a weighted Voronoi diagram and they used minimum users' loss as the objective. Mak et al. (2013) considered a battery-swapping infrastructure planning problem for EVs, the objective of which was to minimise the fixed costs of opening and operating the battery-swapping stations and the expected battery holding costs. Wang (2008) proposed a mixed-integer linear program to minimise the cost of electric scooter battery exchange stations for tourism transport with the consideration of various factors such as a battery's maximum range, the size of ES fleets, location capacity, and service capacity. Wang and Lin (2013) considered multiple types of EV charging stations of heterogeneous recharging rates and demonstrated that the use of mixed stations was more cost-effective than using only a single type of recharging station. Jung et al. (2014) proposed a bi-level simulation-optimisation approach to determine the EV charging locations. The objective of the upper level was to minimise the total queue delay and travel time, while on the lower level the objective was to minimise passenger waiting time and travel time. He et al. (2015) considered the drivers' spontaneous adjustments and interactions of travel and recharging decisions. Their goal was to minimise the sum of total driving and recharging time, and the cost incurred by missed trips.

In this paper, contextual, institutional and spatial factors are incorporated to estimate the EV charging demands of locations. The effectiveness of three different facility location models (*i.e.*, SCP, MCLP, and PMP) will be compared. Flow-capturing models are not considered in our analysis due to the unavailability of an original–destination (OD) traffic matrix, which is a main challenge when applying FCLM and FRLM.

3. Methodology

3.1. Study area

As the capital city of China, Beijing has 16 districts and its total resident population was approximately 20 million in 2010. Beijing is a pilot city for the promotion of EVs and consumers are eligible for subsidies from both the central and local governments. Since the city government gives more encouragement to the promotion of pure battery EVs over other vehicle types, due to the urgent need to improve the city's air quality, more charging facilities will be needed in the future. Good access to public charging infrastructure will be extremely important in Beijing to encourage EV adoption. Considering the local travel profiles and the range of available EVs, the local governments of Beijing expect to install public charging facilities every 5 km, which feature is highlighted in the *Action Plan of Beijing for Promoting EVs (2014-2017)*. It is expected that in 2017 there will be 107 charging/battery swap stations. Because the urban area of Beijing has little vacant land, according to the Beijing Municipal Administration of Quality and Technology Supervision, the newly constructed charging stations should take advantage of the existing service facilities such as petrol-refuelling stations.

3.2. Estimation of EV demand

As a relatively new product, EV adoption is not likely to be evenly distributed across the study area. We estimated the EV demand in two steps. Firstly, we identify key attributes to characterise the EV early adopters from research literature (Curtin et al., 2009; Campbell et al., 2012; Chiu and Tzeng, 1999; Egbue and Long, 2012; Gong et al., 2013; Hidrue et al., 2011; Erdem et al., 2010; Mabit and Fosgerau, 2011; Potoglou and Kanaroglou, 2007; Zhang et al., 2011, 2013). To examine whether these factors are relevant to China, the research team conducted interviews with government officials and experts familiar with the EV markets in Beijing and Shenzhen, China, from August 2014 to January 2015. Based on the literature review and fieldwork, we selected six key socio-demographic attributes to estimate EV demand, namely, income, vehicle ownership, educational level, age, gender, and family size.

Secondly, we used the ranking-type Delphi method to identify the relative importance of selected variables influential to EV adoption. The Delphi method was developed by the RAND Corporation in the 1950s and it has been widely used to obtain consensus from a group of experts. This method is especially useful in a situation where there is limited empirical evidence or inadequate statistics in the study area (Dalkey, 1969; Gupta and Clarke, 1996; Okoli and Pawlowski, 2004; Schmidt, 1997). According to a review conducted by Pare et al. (2013) that covered 42 publications, the majority of ranking-type Delphi surveys reported a small sample size (*e.g.*, 7–30). In our study 11 representatives (*i.e.*, A–K) were invited to rank the relative importance of each attribute. The final ranking and weighting results are shown in Table 1. The number 1 represents the most important, and the number 6 represents the least important. Kendall's W coefficient of concordance (Kendall, 1948; Siegel, 1956) was calculated to check the consistency of the collected ranking. The W value for the last round survey is 0.54 and it is higher than the critical value 0.491 ($\alpha = 0.025$), which indicates strong agreement of the experts' judgments. So the null hypothesis is rejected and the rank results can be used to calculate the weighting score of each attribute. The relative importance of these socio-demographic attributes is consistent with that revealed by previous studies (Caulfield et al., 2010; Curtin et al., 2009; Zhang et al., 2011).

The final weighting score w from Table 1 was used to estimate the demand. Ideally, the estimation of the exact value of the charging demand should incorporate information of both EV characteristics (*i.e.*, type and size of EVs, and battery capacity) and driving characteristics (*i.e.*, travel time, and travel distance) (Chen and Liao, 2013). However, this type of information is difficult to obtain at the early EV penetration stage (Parker et al., 2012). Hence, we use a weighted population in each census tract as a proxy to estimate the potential charging demand (Giménez et al., 2014; Lam et al., 2013). Since most research is targeted on the population older than 18 (*e.g.*, Baptista et al., 2012), the demand for EVs is estimated based on the population aged 20 or over. In order to eliminate the impact of the unit and to keep the linear relationship of the data at the same time, normalisation was used to standardise the kth variable into a range between 0 and 1, which is denoted by f_k. The EV charging demand h of community (*i.e.*, approximated by census tract) i is estimated by:

$$h_i = g_i \sum_k w_k f_{ki} \tag{1}$$

where g_i is the targeted population (*i.e.*, aged 20 or over) of a community i, w_k is the relative importance of the kth selected socio-demographic variable, $\sum_k w_k f_{ki}$ represents the EV adoption potential index of a community i. Information of these socio-demographic variables is drawn from two sources: income and vehicle ownership information is obtained from *the 2011 Beijing Statistical Year Book* at district level, and other variable information is taken from *the Sixth National Population Census of 2010*.

Based on our analysis, residents living in the inner city areas are more likely to buy an EV, which generates a higher demand for public charging facilities. This is consistent with our expectation because downtown Beijing has a high concentration of car owners, high-income households, and a well-educated workforce, all of which are significant determinants of EV adoption.

3.3. Potential sites of EV charging stations

Public charging stations in urban areas aim to serve private vehicles; therefore, they should be located in places with easy public access and high visibility. Public charging facilities deployment, which began quite recently in Chinese cities, struggles to optimise their location in an already dense urban area. As pointed out by a public charging facility investor in Beijing, 'It is quite difficult to find vacant space for the construction of public charging stations. Furthermore, the land use for facility construction needs to be approved by the local government first and such a process will take approximately two years, which is too long a period for most investors.' Some investors may consider constructing the charging facility on temporarily vacant land rented from the government; however, because charging facility deployment is not at present formally incorporated into the urban planning system, 'The Government still has the authority to plan another use for the land; in which case, these charging facilities will have to be torn down, which would result in a great loss of capital investment.' These views were expressed by a public charging facility investor and a government planner.

Table 1
Ranking of socio-demographic variables.

Interviewee	Income	Vehicle ownership	Educational level	Family size	Age	Gender
A	1	3	2	5	4	6
B	1	2	4	3	5	6
C	1	2	3	4	5	6
D	3	2	5	4	1	6
E	4	3	5	2	1	6
F	4	3	2	1	5	6
G	3	1	4	5	2	6
H	2	1	3	6	4	5
I	2	1	5	3	4	6
G	1	2	3	4	6	5
K	2	1	3	6	4	5
R	**24**	**21**	**39**	**43**	**41**	**63**
Final weighting score *w*	**22.90%**	**24.20%**	**16.50%**	**14.70%**	**15.60%**	**6.10%**

Note: *R* is the sum of ranking.

In view of the space constraints, a practical alternative is to take advantage of existing infrastructure to install public charging facilities. The government has made suggestions regarding potential locations for the installation of public charging facilities. According to the *Action Plan of Beijing for Promoting EVs (2014–2017)*, announced by the Beijing government in 2014, these locations include EV 4S shops, public car parks, universities, and petrol-refuelling stations. From the geographical perspective, these locations are usually in safe and accessible areas. In fact, the suggested location types are also common, potential location sites for public charging facilities' deployment in other cities (Chen and Hua, 2014; Sweda and Klabjan, 2011; Wang et al., 2010).

In this study, the potential location sites include petrol-refuelling stations from SINOPEC (China Petroleum & Chemical Corporation) and CNPC (China National Petroleum Corporation), as well as the public car parks of two big parking companies (*i.e.*, *BJGL Anda Parking Management* and *Beijing Kingdy Parking Management*). Other public car parks will not be considered at this stage due to their relatively small scale. For safety reasons, charging points should be located at least 6 m away from petrol-refuelling equipment, and the station should also be adequately spacious (*i.e.*, larger than 1500 m^2) to provide parking space. Therefore, petrol-refuelling stations within the Third Ring Road are excluded in this analysis since they can hardly meet this size requirement according to the suggestion of a SINOPEC station manager. In total, there are 313 demand points[3] and 1029 possible locations for charging stations. The spatial distribution of the demand points and potential sites is presented in Fig. 1.

3.4. Model descriptions

In this section, we will use the demand points and their estimated EV demand along with the location of charging stations to conduct a case study of Beijing by using the three facility location models.

3.4.1. The set covering model

In research literature, the SCP model has been widely adopted for facility location problems. The notations used in SCP in an EV charging station setting are listed as follows.

Sets and parameters:

I = the set of demand points;
J = the set of potential locations of charging stations;
d_{ij} = the Euclidean distance between demand point i and charging station j;
D = the critical coverage distance or radius, which is defined as the maximum Euclidean distance that a charging station can serve a demand point; and
$N_i = \{j \in J : d_{ij} \leqslant D\}$, *i.e.*, the set of charging stations that are within the critical coverage radius of demand point i.

Decision variables:

$$x_j = \begin{cases} 1, & \text{if charging station } j \text{ is established;} \\ 0, & \text{otherwise.} \end{cases}$$

The formulation of the set covering model is as follows.

[3] There were 325 census tracts in 2010 and 313 census tracts in 2006. We have only the 2006 census boundary so the 2010 census data were converted to 313 tracts.

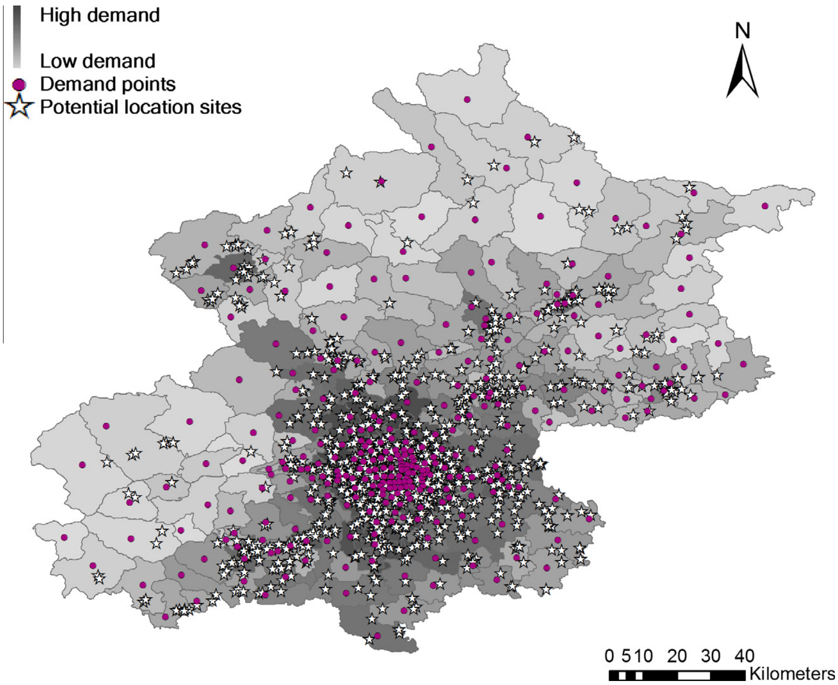

Fig. 1. Locations of potential sites and demand points of public charging stations.

Formulation:

$$\min \quad \sum_{j \in J} x_j \tag{2}$$

$$\text{subject to}: \quad \sum_{j \in N_i} x_j \geqslant 1 \quad \forall i \in I \tag{3}$$

$$x_j \in \{0, 1\} \quad \forall j \in J \tag{4}$$

In the set covering model, objective (2) is to minimise the number of charging stations needed to serve all the demand points. Constraints (3) ensure that each demand point can be served by at least one charging station within the critical coverage radius. Constraints (4) state that the decision variables can only be binary. In this paper, we adopt Euclidean distances (in km) as the distances between the potential charging stations and the demand points.

Although the SCP model is very popular for facility location problems, it does not take into account the level of demand by the community; all the demand points are treated as equally important in the model. Another shortcoming of the set covering model is that a solution is feasible only if all the demand points are covered. However, in practice, governments and organisations may have only limited budgets to establish the charging stations so that the number of facilities to be built will be limited. Moreover, the problem becomes impractical when none of the potential locations for the facilities is within an acceptable distance from a community.

3.4.2. The maximal covering location model

MCLP model is another popular one for facility location planning. MCLP is similar to SCP in that a demand point is considered to be covered if it falls into the critical coverage radius of an established facility, but it is more realistic in the sense that it incorporates a budgetary constraint to limit the number of facilities to be built and it does not require all the demand points to be covered. The additional notations used in MCLP in an EV charging station setting are listed as follows.

Additional parameter:

p = the number of charging stations to be established.

Additional decision variables:

$$z_i = \begin{cases} 1, & \text{if demand point } i \text{ is covered;} \\ 0, & \text{otherwise.} \end{cases}$$

The formulation of the set covering model is as follows.

Formulation:

$$\max \quad \sum_{i \in I} h_i z_i \tag{5}$$

$$\text{subject to}: \quad \sum_{j \in N_i} x_j \geqslant z_i \quad \forall i \in I \tag{6}$$

$$\sum_{j \in J} x_j = p \tag{7}$$

$$x_j, \ z_i \in \{0,1\} \qquad \forall i \in I, \quad j \in J \tag{8}$$

In MCLP, objective (5) maximises the total level of demand that can be covered. Constraints (6) state that a demand point can be covered only if at least one charging facility within the critical coverage radius is built. Constraint (7) requires that exactly p charging facilities are built. Constraints (8) state that the decision variables are binary.

Although MCLP is more realistic than SCP since (i) the budget can be specified (assuming that the costs of building all facilities are the same), (ii) not all the demand points are necessarily to be covered, and (iii) the level of demand of each community is considered, similar to SCP, the degree of convenience for EV drivers to access the charging facilities is not recorded. The distance between a charging station and a community has only a binary effect: either the charging station can serve a demand point, or it cannot. If a demand point can be covered, the distance from the nearest station is not a concern. However, to effectively set up the EV charging stations, one may wish to establish them in such a way that these charging facilities are closer to communities with a high EV charging demand. From this aspect, the formulation that PMP can consider is an enhanced model of MCLP.

3.4.3. The p-median model

The p-median model requires the following additional decision variables.

Additional decision variables:

$$y_{ij} = \begin{cases} 1, & \text{if station } j \text{ is the closest established charging station to demand point } i; \\ 0, & \text{otherwise.} \end{cases}$$

An integer programming formulation of the p-median model for the EV charging station allocation problem is as follows.

Formulation:

$$\min \quad \sum_{i \in I} \sum_{j \in J} h_i d_{ij} y_{ij} \tag{9}$$

$$\text{subject to}: \quad y_{ij} \leqslant x_j \qquad \forall i \in I, \quad j \in J \tag{10}$$

$$\sum_{j \in J} y_{ij} = 1 \quad \forall i \in I \tag{11}$$

$$\sum_{j \in J} x_j = p \tag{12}$$

$$x_j, y_{ij} \in \{0,1\} \qquad \forall i \in I, \quad j \in J \tag{13}$$

Objective (9) aims to minimise the total demand-weighted distance between the demand point and the closest established charging facility among all possible pairs. By minimising Objective (9), the established charging facilities will tend to be closer to communities with high EV charging demand in an optimal solution. Constraints (10) ensure that charging station j cannot be assigned to demand point i if it is not established. Constraints (11) state that there is one, and only one, closest established charging station to each demand point. Constraints (12) ensure that there are exactly p charging stations to be established. Constraints (13) state that the decision variables can only be binary.

Because the purpose of Objective (9) is to minimise the total demand-weighted distance between the demand point and the closest established charging facility among all possible pairs, PMP produces an optimal solution that tends to establish charging facilities closer to communities with high EV charging demand. As a result, PMP provides an optimal solution that is more convenient for the majority of EV drivers.

4. Results

In this section, we compare the solutions produced by SCP, MCLP and PMP, and then we examine the effect of adjusting the number of EV charging stations. In all the computation experiments, we used CPLEX 12.6.1 as our integer linear programming solver. All the computational tests were performed on an Intel(R) Core(TM) i5-4570 3.20 GHz personal computer with 16.0 GB of RAM.

In the SCP and MCLP, we set the critical coverage distance to 5 km, *i.e.*, $D = 5$. In SCP, with $D = 5$, there are some demand points that cannot be served by any one of the potential charging stations and the constraints associated with these demand points were removed from the model to guarantee the problem feasibility. Then, we solved SCP and obtained an optimal

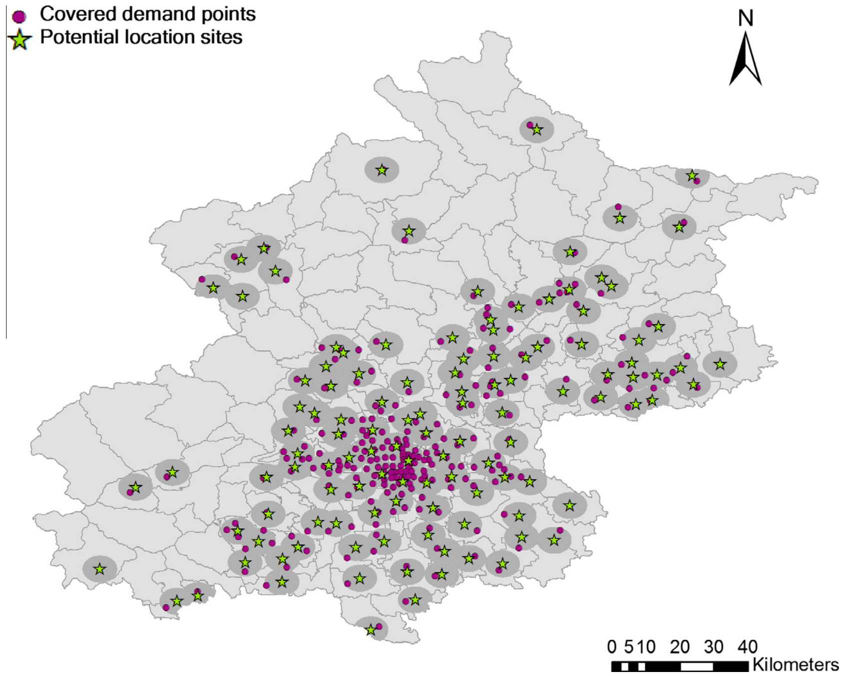

Fig. 2. Locations of EV charging facilities determined by SCP.

value of 118, *i.e.*, 118 EV charging facilities are sufficient to cover all the remaining demand points. The locations of the charging stations are shown in Fig. 2.

With the number of EV charging facilities equal to 118, we solved the MCLP and PMP and obtained the optimal locations of EV charging facilities that minimise their objectives. The locations of their charging stations are shown in Figs. 3 and 4. We found that SCP and MCLP produce very similar results (where 83 out of 118, *i.e.*, 70.34%, of their optimal locations of charging stations are the same); they both suggest charging facilities that are more spread-out. PMP has a very different result from SCP and MCLP (where PMP has only 26 and 22 stations in common with SCP and MCLP, *i.e.*, 22.03% and 18.64% of the common stations, respectively) and this suggests that the stations are closer to the points of high EV charging demand. Thus, PMP can determine the location EV charging stations that would be more accessible for the majority of potential EV users.

The benefit of using PMP can be further affirmed from Figs. 5a and 5b, which show the total number of demand points covered by the 118 optimal EV charging facilities previously found by each model and their total covered charging demand within various coverage distances. Because SCP and MCLP suggest a high proportion of common charging facilities, their representative lines in Figs. 5a and 5b are very similar and overlap in several segments. In both figures, we observe that SCP and MCLP have a very ‘sharp’ change at the critical coverage distance of 5 km, while the lines of PMP are smoother. This is due to the fact that SCP and MCLP focus only on whether a demand point is within 5 km of any charging facility; how far apart they are is not a concern as long as the distance is not more than 5 km, while the absolute distance is a factor to minimise in the objective of PMP. In Fig. 5a, we observe that significantly more demand points can be covered by the PMP charging stations within a shorter coverage distance range (from 1 km to 4 km), compared with the SCP and MCLP solutions. Although for a critical coverage distance of 5 km or longer, the SCP and MCLP charging facilities cover more demand points than the ones of PMP, their total covered EV charging demands are very close (the difference is approximately 5.74%). This indicates that the suggested sets of EV charging station locations by the three models can cover similar levels of demand, within the critical coverage distance of 5 km. In Fig. 5b, for a coverage distance ranging from 1 km to 4 km, a significantly higher total covered EV charging demand can be captured by the optimal PMP charging stations. With the EV charging facilities closer to the communities with high EV adoption intensity, this will definitely encourage the majority of EV drivers to keep travelling by EVs and also encourage other people in the area to consider adopting EVs for transportation. From a management perspective, having more charging facilities set up in the high demand areas, as suggested by the PMP model, may be beneficial in terms of power management of the electricity grids (Gurkaynak and Khaligh, 2009). This facility distribution scheme can better respond to the event of facility disruptions since a demand point is close to multi-charging stations simultaneously (Berman et al., 2009; Daskin, 1983; ReVelle and Hogan, 1989). The idea of centralized location has also been applied to the location–allocation problems of other public facilities. For example, Berman et al. (2007) suggested that four general hospitals in Toronto be located within a few city blocks of downtown with high demand leaving vast areas of the city with no general hospitals at all.

We note from the literature that the critical coverage distance has been an important aspect in determining EV charging facility locations. For example, Upchurch and Kuby (2010) adopted FRLM and considered a vehicle range of 100 miles (*i.e.*, a

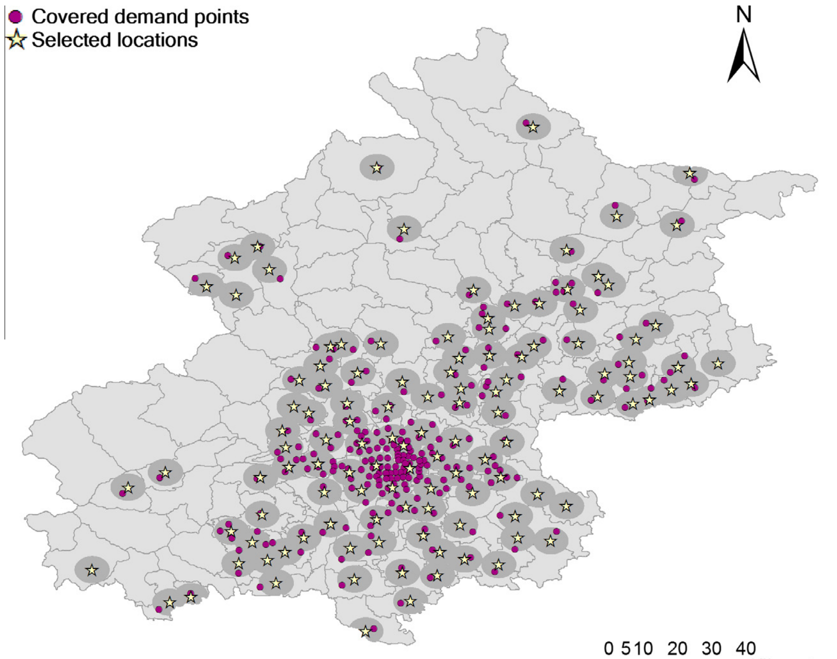

Fig. 3. Locations of EV charging facilities determined by MCLP.

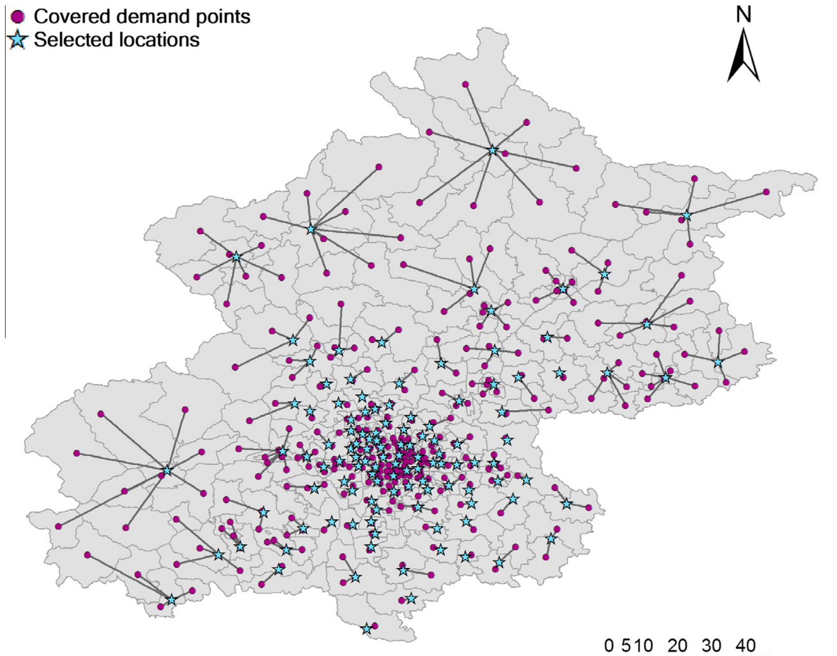

Fig. 4. Locations of EV charging facilities determined by PMP.

vehicle can travel 100 miles on a full charge) to determine optimal locations of EV charging facilities in Orlando, Florida. In the next few years, the advances in EV technology are expected to be very fruitful. For instance, Nissan is working on a next-generation battery that can achieve a vehicle range of 310 miles per charge (Greimel, 2015). We observe from Figs. 5a and 5b, for a coverage distance of 5 km or further, SCP and MCLP appear to cover increased demand. We also report that using the data of our case study, in terms of coverage (*i.e.*, the number of demand points and the level of demand covered), the

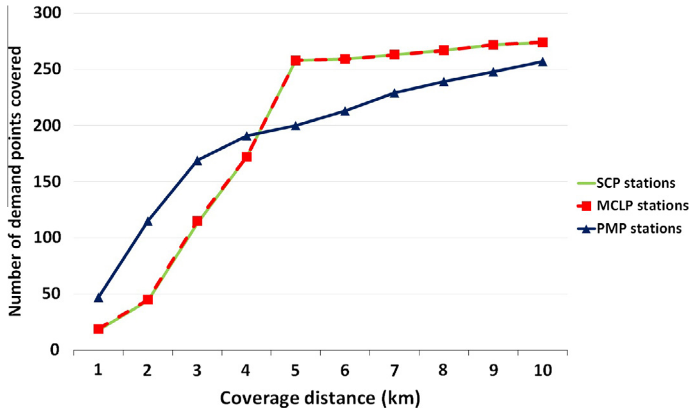

Fig. 5a. Number of demand points that are covered by establishing the 118 charging stations suggested by the three models vs various coverage distances.

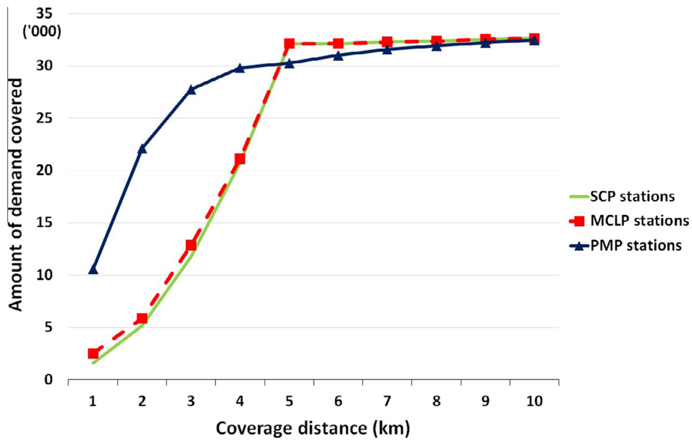

Fig. 5b. Level of demand that is covered by establishing the 118 charging stations suggested by the three models vs various coverage distances.

effectivenesses of the three models for longer coverage distances, *e.g.*, 15 km and 20 km, are very comparable: the differences between three models in the two measures are less than 3%. However, for highly compact cities, such as Beijing, battery capacity may not be a crucial factor that impacts the spatial planning of charging facilities because residential and commercial areas are mostly located within a reasonable vehicle range; instead, the convenience of access to charging facilities is the major concern. If the distance to the nearest station is too far, potential EV users may give up the adoption of EVs. Thus, in our study, we focus on the performances of the three models with shorter coverage distances, which focus is in line with the Municipal's spatial planning scheme in which the service radius of refuelling stations is anticipated to range from 0.95 km to 4.94 km (Beijing Municipal Amenities Committee, 2009). With an increasing number of EVs in the future, a higher density of charging facility is expected in order to meet the growing charging demand. For instance, a service radius of 2 km for charging stations in Beijing is suggested in a study by Liu (2012). In such cases, the coverage of EV charging facilities for a distance of 5 km or longer may become less relevant. From this perspective, PMP appears to be more effective for determining EV charging station locations.

In practice, governments and organisations may have only limited budgets to establish EV charging stations and, thus, the number of facilities that can be built is limited. We conducted another set of computational experiments using MCLP and PMP to examine the effect of varying the number of EV charging stations. The SCP solution (with 118 charging facilities) was also used for reference. This practice can facilitate the cost-effectiveness analysis of the EV charging stations' planning. In this set of computational experiments, we increased the maximum number of EV charging stations to be established from 20 to 200, with an increment of 20 stations for each instance, *i.e.*, $p = 20, 40, \ldots, 200$. In this experiment, we recorded (i) the number of covered demand points (*i.e.*, Objective (2)), (ii) the maximum distance from a demand point to the nearest established charging facility, (iii) the amount of covered demand (*i.e.*, Objective (5)), and (iv) the demand-weighted distance (*i.e.*, Objective (9)). Their figures are respectively shown in Figs. 6a–6d. For measures (i) and (iii), again, the critical coverage radius we used was 5 km.

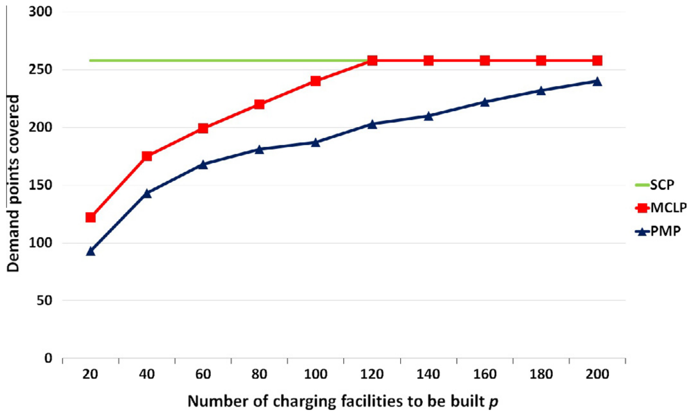

Fig. 6a. Number of demand points covered vs number of EV charging stations.

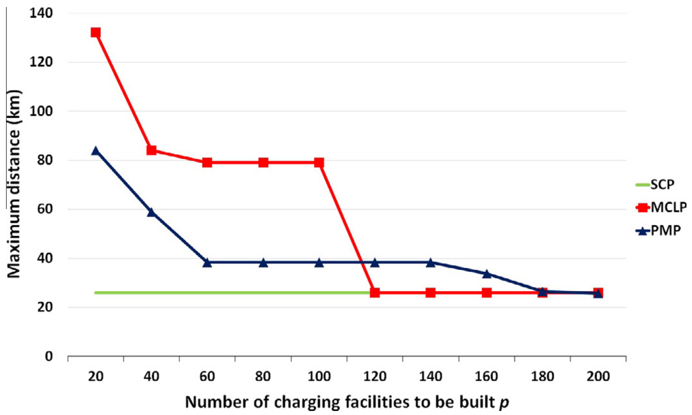

Fig. 6b. Maximum distance from a community to the nearest established charging facility vs number of EV charging stations.

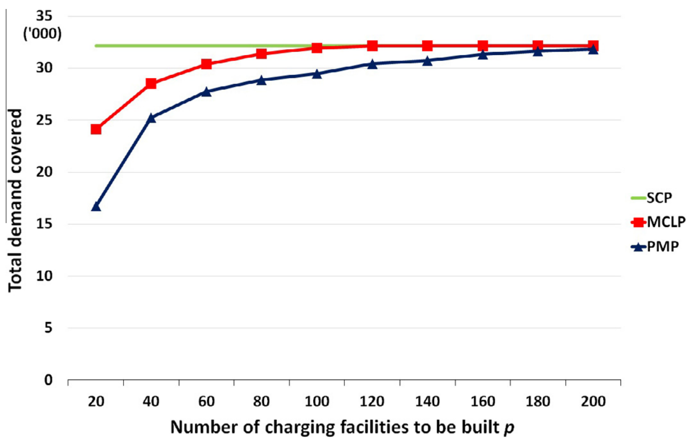

Fig. 6c. Total level of demand covered vs number of EV charging stations.

For measures (i) and (ii), we aim to investigate how well the two models perform in terms of equity. From Fig. 6a, we observe that MCLP covers more demand points (with an average of 20.68%) than PMP does; this is because SCP and MCLP have a high number of common locations for EV charging stations. MCLP covers the same number of demand points as SCP when $p \geqslant 120$, whereas PMP cannot cover so many even when $p = 200$. This indicates that PMP does worse for covering demand points, because it tends to build charging stations near the communities of high demand but neglects others of low

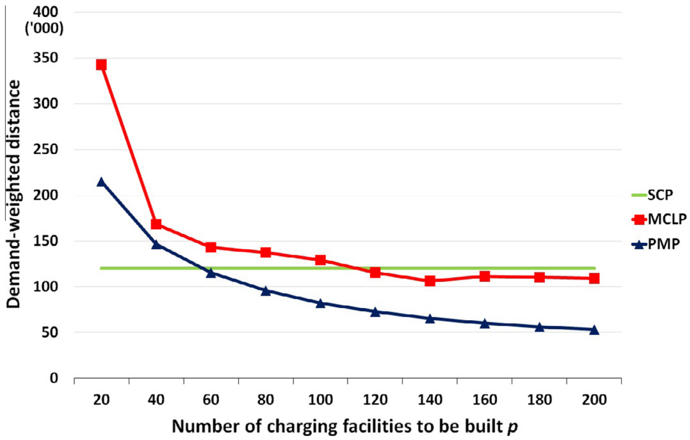

Fig. 6d. Demand-weighted distance vs number of EV charging stations.

demand. However, in Fig. 6b, PMP appears to achieve a shorter maximum distance between a demand point and its nearest established charging station (with an average of 9.42% shorter) than MCLP, particularly when $p \leqslant 100$. This is due to the fact that PMP minimises the demand-weighted distance which tends to avoid allocating a community to a distant charging station. On the other hand, MCLP captures distance in such a way that a community is considered to be covered within the coverage distance; but the information about how far a distant station is located from the community does not matter as long as it is within the coverage distance. Thus, the optimally selected charging stations from PMP are more conveniently accessible among all communities in terms of the longest travel distance.

For measures (iii) and (iv), we aim to assess how well MCLP and PMP perform in satisfying the other's objective. In Fig. 6c, MCLP performs better than PMP on its own objective; it covers a higher level of demand, with an average of 9.90% more across all instances. As shown in Fig. 6d, PMP does better than MCLP on its own objective: the demand-weighted distance of PMP is less than the one of MCLP, with an average of 35.74%. Although the observation that both models perform better on their own objective is not surprising, the percentage gaps between the two models in Figs. 6c and 6d suggest that PMP does considerably better on the MCLP's objective than MCLP does on the PMP's objective.

In Figs. 6a–6d, we also observe that, in general, the marginal increases/decreases in these measurements are greater when the number of EV charging facilities to be established is small, while they tend to be less as we increase this number. This result is expected because the contribution of additional resources would be insignificant when the resources are close to being saturated.

We report the number of demand points and the level of EV charging demand covered by MCLP and PMP charging stations in Figs. 7a–7d. As expected, the curves of $N = 120$ in these figures are similar to their respective curves of $p = 118$ in Figs. 5a and 5b. From Figs. 7a–7d, we again observe the 'sharp' shape of MCLP lines at $D = 5$ and the smooth PMP lines. Figs. 7a and 7b, respectively, show the MCLP and PMP curves of the number of covered demand points versus the critical coverage radius. Similar to what we previously observed for $p = 118$, the effect of increasing the number of EV facilities is more significant when p is small and then becomes less when this number is large. Figs. 7c and 7d show clearer pictures to determine the critical point that increasing the number of EV charging facilities does not give much significant improvement in terms of the total covered EV charging demand. In both figures, starting from 160 EV charging stations, the curves are approximately the same as the others when increasing the number of stations. Figs. 7c and 7d are also helpful for policymakers in the sense that the effect of changing the number of EV charging facilities on the demand to be covered within various distance ranges can be easily examined. Our approach that integrates location models with contextual factors can, therefore, provide policy-makers with a convenient and effective way of conducting a cost-effectiveness analysis and of understanding the additional benefit of increasing the number of EV charging facilities.

Another important aspect for choosing the EV charging station locations is the stability of solutions (Upchurch and Kuby, 2010); this is because governments and organisations may wish to establish the locations progressively in multiple phases. By stability, we mean how likely an optimal charging station remains in the choice set when the number of charging facilities to be built increases. The relocation of charging stations will incur additional costs for the removal and reconstruction of facilities. Therefore, the more stable the solution, the better is the planning of the EV charging infrastructure. Figs. 8a and 8b show, respectively, the percentages of optimal MCLP and PMP EV charging stations remaining optimal when increasing the number of charging facilities to be built from p to p'. The higher the curve, the more stable is the solution. In both figures, we observe that the curves of different values of p appear to be 'U-shaped'. This indicates that, in general, the solution is more stable when the increment of the number of charging stations is either low or high; but when the increment is moderate the locations can be very different. This phenomenon may be due to the fact that when the change in the number of charging stations is not significant then the choice of locations should be similar, and when there are more facilities to be built;

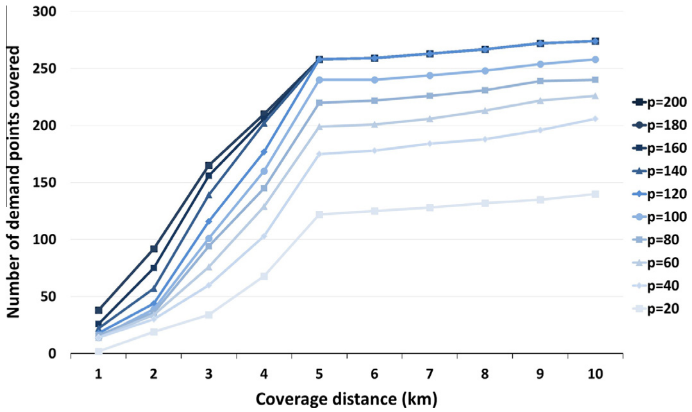

Fig. 7a. Number of demand points that are covered by establishing p charging stations using MCLP vs various coverage distances.

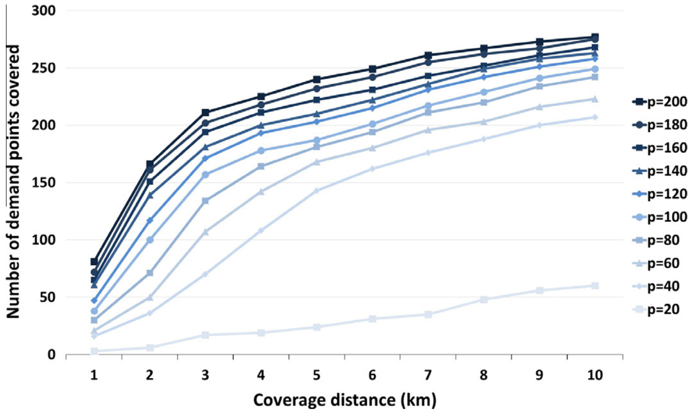

Fig. 7b. Number of demand points that are covered by establishing p charging stations using PMP vs various coverage distances.

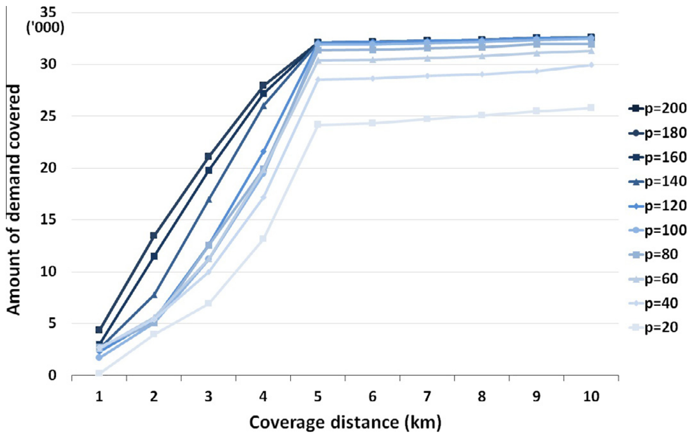

Fig. 7c. Level of demand that is covered by establishing p charging stations using MCLP vs various coverage distances.

therefore the originally determined stations are more likely to be chosen again. When the change is significant but the number of charging stations to be built is not sufficient, then the models can suggest very different results. Another observation is that the curves are higher for large p. This means that solutions are more stable if the number of EV charging stations to be built is large. This may be due to the fact that the objective function is hard to improve for large p (please refer to the MCLP curve in Fig. 6c and the PMP curve in Fig. 6d), and therefore the choice of locations should be similar. From Figs. 8a and 8b, it appears that PMP is more stable (*i.e.*, its respective curves are higher) in general and particularly when p is large.

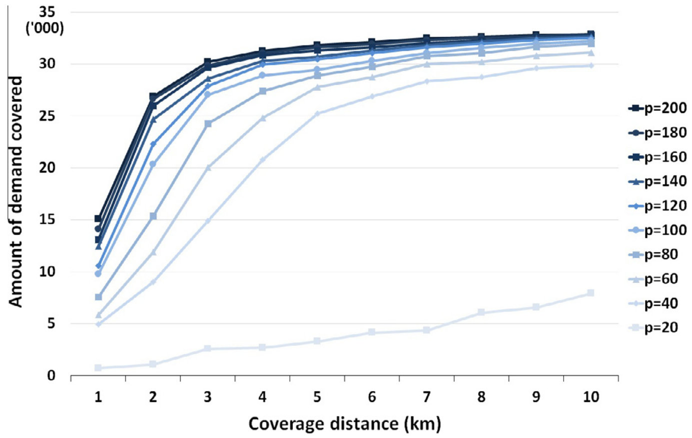

Fig. 7d. Level of demand that is covered by establishing p charging stations using PMP vs various coverage distances.

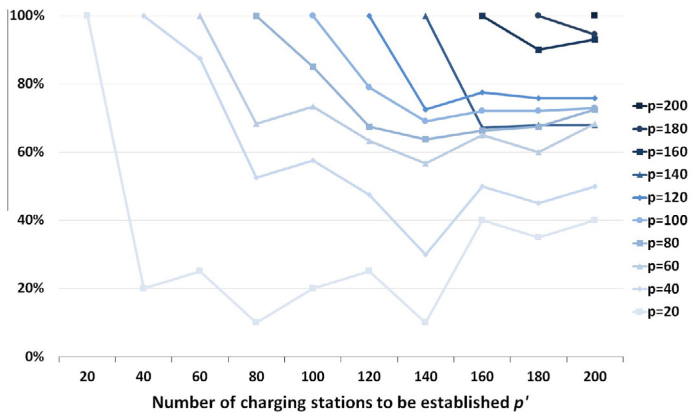

Fig. 8a. Percentage of optimal MCLP EV charging stations remaining optimal when increasing p to p'.

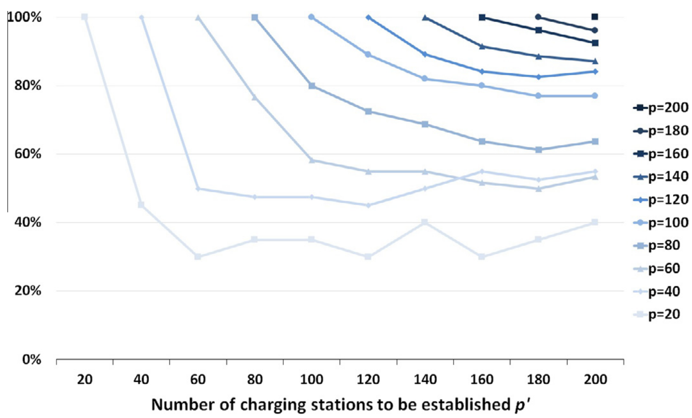

Fig. 8b. Percentage of optimal PMP EV charging stations remaining optimal when increasing p to p'.

5. Conclusions

In this study, we argue that contextual factors matter in the location–allocation problems of public EV charging stations because the demand and supply of these stations will vary across different countries and regions. Therefore, our first objective in this study is to incorporate the contextualised institutional and spatial constraints of Beijing in the deployment of EV public charging stations. From an institutional perspective, because the deployment of charging stations in Beijing is still based on a top-down approach, the regulations and policies serve as a principle that needs to be followed in practice. Hence, in our models we carefully select the potential sites and also target the service radius of the charging stations. From a spatial perspective, given that Beijing still has a largely monocentric urban structure, the city centre is expected to generate a high demand for EV due to the socio-demographic profile of the residents. Together with the contextualised factors taken into account, our research will be useful for government and business sectors that aim to improve the effectiveness of the spatial planning for public EV charging stations.

Our second objective is to compare the optimal locations from three classic facility location models: the set covering model; the maximal covering location model; and the *p*-median model. Our computation results show that the *p*-median model is more effective than the other two models for facility location decisions for public charging station planning in the sense that the suggested public charging facilities are more convenient for the population with a higher EV charging adoption intensity. Considering the government's goal of satisfying the charging demand within 5 km, *p*-median charging stations are distributed mainly in the city centre as well so that areas with high demand can be served better within relatively short distances (*i.e.*, 1–4 km). We believe that high accessibility to EV charging stations would encourage drivers to adopt EVs for transportation and also encourage existing EV users to continue driving EVs. Our results also suggest that the *p*-median model performs better than the maximal covering location model in terms of satisfying the objective of the other model. In terms of stability, we found that when the number of charging stations to be built is large, or when the relative changes are minor, the solutions to both models are more stable as p increases. Finally, we also demonstrate in the present paper how to use our approach to analyse the cost-effectiveness of establishing different numbers of public EV charging facilities.

This study can be further improved in a number of ways. Firstly, the 52 pilot stations were taken as potential sites rather than as existing public charging stations, and this may result in some of these pilot stations not being selected by our models. Secondly, our demand points were based on the census data of 2010, which can be updated with Census Statistics periodically in the long term. Thirdly, we weighted the six socio-demographic factors based on interviews with a relatively small sample size. A large-scale questionnaire survey can be conducted to gain a better understanding of the contextual factors in EV adoption in our study area.

In the future, more research needs to be carried out to further study the deployment of charging stations with special consideration of the local institutional and spatial settings, and this would make the facility location models more pragmatic and policy-relevant. The outcomes may help not only the popularisation of EVs but may also help to achieve low-carbon transport in our urban systems.

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