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# Solving Location Problem for Electric Vehicle Charging Stations–A Sharing Charging Model

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**ABSTRACT** Sharing charging stations are an effective solution for daily usage of electric vehicles charging, however, the area with high demand cannot provide enough stations while there are plenty of stations left idle in remote areas with less demand. The core of the problem is the imbalance of demand and supply. In other word, we need to allocate the charging station to the appropriate locations to balance demand and supply. This study aims to solve the problem of locating charging stations for public electric vehicles (PUEVs), to improve the sharing charging level. We take into consideration the factors affecting charging station locations including mileage, PUEV distribution and passenger distribution. A Non-deterministic Polynomial (NP) model aiming to minimize the total vehicle service distance is developed. We use an agent-based model to simulate the optimized charging station location based on Anylogic. Through a case study of Beijing, we test the model in five situations. This paper concludes that priority, mileage, PUEV distribution and passenger distribution are the key factors affecting the location of PUEV charging stations, with exogenous variables such as the type of circuit and the voltage drawn as constants. The results of one situation show that the existing layout of the charging stations is unreasonable when charging frequency is sharply variant; this paper optimizes the existing location by improving the constraint for the smallest number of charging stations; the proposed model can be used for EV charging stations' location in densely populated metropolis.

**INDEX TERMS** Agent, charging frequency, sharing charging, electric vehicles, location.

## I. INTRODUCTION

Recently, sharing economy is no longer a new phenomenon to us. It has been influencing our life to the extent that it has become a part of our life. From the emergence of shared cars, to shared umbrellas, shared portable chargers, shared storage, etc., a new generation of sharing goods has arrived (Gong *et al.*, 2018). One of the characteristics of sharing economy is that customers do not need to purchase the product (such as bicycle) before using it. This novel way of consumption makes peoples' life more convenient, and it also tremendously improves the utilization of some resources left idle (Burinskiene *et al.*, 2018).

Sharing economy has changed our lifestyle and the way we think, e.g. shared bicycles reduced the traffic jam to some extent, which helps with maximizing the utility of the public roads. The car-sharing, toy-sharing platforms are beneficial for re-allocating the resources laying idle, so that people can afford to share these goods with a reasonable price–this is also a concrete representation of the ''internet +'' thinking mode in our life. The development of commercial economy, the maturing of mobile internet techniques and the improvement of people's living quality all accelerate the changing of people's perspectives on the relationship between people and products: people become to value utilizing and enjoying the product more than owning them. More people start to consider about how to live a life in which they can freely choose the products that they like. This is the lifestyle of reduction – and this is exactly the internal force that has been driving the emergence and developing of sharing economy.

In terms of the automobile industry, with the popularization of alternative energy vehicles, the number of alternative energy vehicle owned in China has been skyrocketing due to the government's encouragement (Gong *et al.*, 2019).

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According to the data from China Association of Automobile Manufactures, the amount of owned alternative energy vehicles in China reached 1,729,000 until 2017; the number of battery electric vehicles reached 800000. In 2017, The annual production of alternative energy vehicles was 794,000, and the annual sales hit 777,000: which respectively increased 53.8% and 53.3% comparing to last year. However, the development of alternative energy vehicle industry is held back by the insufficient amount of charging stations, which has become the Achilles heel of the industry. According to the statistics, until 2017, the number of public charging stations in china was 213,903; the number of private-owned charging stations (comes when purchasing cars) was 231,820 – there are 3.8 more times of cars to charging stations; while this rate for battery electric cars to their charging station is 1.8:1. 90% of the potential AEV owners have to give up purchasing the car because of the insufficient amount of charging stations. Many customers' requests for installing charging stations were often declined by property management companies, and the reasons were the insufficient amount of parking spots or safety issues. Even though the installation of public charging stations is common in first-tier and second-tier cities, these stations are only capable of dealing with emergencies – they are not a solution for daily usage. Therefore, facing this awkward situation, charging station companies come up with a brand-new charging concept: shared charging stations.

As known, the symbol of sharing economy – sharing bicycles has caused tremendous waste of society resources due to the flooding in of capital. Some wasted bicycles even became a disaster for cities. According to previous research, the number of shared bicycles put to use has reached 2000000. These bicycles will turn into 300000 tons of wasted metal after they became abandoned. It is hard to anticipate what percent of those metal can be reused completely in the following recycle process. Ever since the emergence of sharing economy, illegally owning, hiding and damaging sharing goods have been occurring frequently. Meanwhile, the relevant managing platform has adopted the management principle of "prioritizing the expanding while overlooking the maintenances", which leads to not having any new breakthrough in the exploration of management principles in sharing economy – this has become a major issue which is affecting the existence of sharing economy. We also analyze the charging dilemma for one charging enterprise. It was found that the distribution of the use of charging piles was extremely uneven (Figure 1). The charging vehicles and the charging time of each station were very different. According to data released by China Electric Vehicle Charging Infrastructure Promotion Alliance, till February 2019, the cumulative number of charging infrastructure was 866,000 units of charging piles in the country, an increase of 76.8% year-on-year. More charging piles does not mean that the problem of charging is solved. On the contrary, due to the excessive pursuit of quantity and neglect of idle stations due to bad allocation, the problem of the charging even get worse. In the long run, it will seriously restrict the

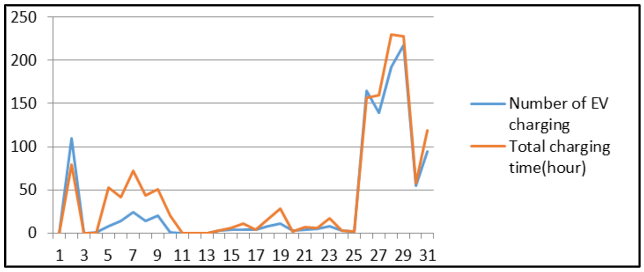



**FIGURE 1. Charging unbalance of charging piles.**

development of the electric vehicle industry. It is urgent to solve the problem of charging balance (charging sharing) during the construction of charging facilities by establishing a scientific method system, avoiding the predicament of sharing bicycles.

Therefore, the purpose of this study is to prevent the development of sharing charging station from going onto the same self-destructive way of sharing bicycles. Especially, to prevent the waste of resources caused by unreasonable allocation (the installation of charging stations) being driven by the flooding of capital. We hope that through this we can discover a management style that can help the spread and operation of the business reach a self-sustainable balance. Therefore, the current research focuses on the decision-making process of company suppliers of the allocation of resources (i.e. the installation of charging stations), in terms of locations. In other word, how to allocate the charging station to the appropriate locations to balance demand and supply.

Sharing charging stations are an effective solution for daily usage of electric vehicles charging, we need to allocate the charging station to the appropriate locations to balance demand and supply. We take into consideration the factors affecting charging station locations including demand priority, mileage, PUEV distribution and passenger distribution, etc. This paper is organized as follows: we first conduct a comprehensive review, which forms the theoretical foundation of this study. In section 3, an analytical model is proposed that forms the base of the research problem. In section 4, we present the Anylogic simulation models. In section 5, we verify the model through simulations with the case of Beijing. Finally, conclusive remarks are presented.

## II. LITERATURE REVIEW

The concept of ownership has been important to customers: as customers, we buy things from stores, we own them – and we are satisfied. The sense of ownership is so important to that that Belk (1988) once associated the things that one person own to the person's identity by claiming: "You are what you own." However, this phenomenon is not necessarily true in this information age anymore. The booming development of information technology, such as computers and internet (especially Web 2.0), has brought "sharing economy" onto the table. This new trend is slowly, but surely changing the business world.

Even though the trend is new, the concept of ''sharing economy'' itself is not. The act of sharing involves ''distributing what is ours to others for their use and/or the act and process of receiving or taking something from others for our use.'' (Belk, 2007) This act has been existing in our society for a long time, since it is presumably driven by evolutionary drive for survival: human share resources, by either exchanging goods or acting altruistically, to better allocate resources, which eventually helps more of their kin to survive (Fine, 1980). The objects for sharing are not confined to tangible goods: intangibles such as music, ideas, values can all be shared (Belk, 2014). We were only able to share those tangibles or intangibles with people close to us, but with the internet, we can share things with people at the other end of the world. The internet provides us with plenty of sharing platform: such as Youtube for video sharing, Spotify and tidal for music sharing, Zipcar for short-term car sharing, Airbnb for accommodation sharing, etc. These platforms significantly improved the efficiency of sharing resources, hence helped with the emergence of sharing economy.

Even though the development of sharing economy has been going on smoothly, defining what exactly sharing economy is can be tricky. According to Hamari, Sjöklint, and Ukkonen (2016), the wide variations in existing terminology creates a difficulty in defining the term: it can be investigated from both socioeconomically and technological aspects; it also has a wide range of manifestations including digital or physical exchange. Researchers indeed came up with a few definitions despite the challenges.

The sharing economy is often referred to as ''collaborative consumptions'' interchangeably in relevant literatures. The earliest definition came from Felson and Spaeth (1978), they defined collaborative consumptions as ''those events in which one or more persons consume economic goods or services in the process of engaging in joint activities with one or more others''. For example, they considered speaking on the telephone, drinking beer with friends as ''joint activities involving consumption''. Alternatively, Botsman and Rogers (2011)defined the concept as ''traditional sharing, bartering, lending trading, renting, gifting and swapping''. However, R. Belk (2014) disagreed with these two definitions. According to him, even though the Felson and Speath's definition emphasized on the joint consumption of products (people consuming things together), it does not involve ''the joint arrangement of the acquisition and distribution of the product'' (Belk, 2014). The Botsman and Rogers'idea (2011) was problematic to them because it is ''too broad and mixes market place exchange, gift giving and sharing'' (Belk, 2014). In other word, this definition is not precise enough.

Belk (2014) himself defined ''collaborative consumption'' as ''people coordinating the acquisition and distribution of a resource for a fee or other compensation, the definition also encompasses bartering, trading, and swapping which involve giving and receiving non-monetary compensation''. This definition excludes behaviors which represents a permanent transfer of ownership, such as gift giving; in turn, it emphasized on the compensation which comes along with the coordinated acquisition and distribution of shared resources (Belk, 2014). Belk's definition corresponds to Bardhi and Eckhardt (2012) idea. They came up with the idea of ''access-based consumption'': instead of paying for the ownership of certain things, consumers prefer to pay for the temporary access to them. Compensation is involved in the process of obtaining the temporary access, which is the essence of Belk's definition. The definition from Hamari*et al.* (2016) is partially congruent with the ones mentioned above. They admitted that ''access over ownership is the most common mode of exchange'', which is similar to Belk's idea. However, they also claimed that the transfer of ownership (such as swapping or donating second-hand things) also counts as a type of collaborative consumption (Hamari *et al.*, 2016).

There are two types of shared charging stations being used now in China: The private charging stations and the charging stations provided by the companies. The plan of sharing private charging station is feasible to some extent. However, the plan of sharing private charging stations is facing these problems: how to deal with the ownership of personal parking spot, and how to have access to the parking lot of the station owners. Therefore, the percentage of private stations available for public utilization is low, which means this ''sharing private stations'' model is not commonly practiced yet. Therefore, this article will not focus on how to share private stations, but instead emphasis on those shared charging stations provided by companies. There are still problems existing in the sharing charging stations business: the area with high demand cannot provide enough stations while there are plenty of stations left idle in remote areas with less demand, optimization should be determined on the basis of the intensity (Zupan *et al.*, 2017). The core of the problem is the imbalance of demand and supply (Gong *et al.*, 2017).

Therefore, we focus on the location of charging stations for PUEVs. The adoption of EVs may be more dependent on the willingness to change from the usual household travel arrangements than on the instrumental characteristics of the vehicle (Tamor *et al.*, 2013). Typically, the locations selected correspond to popular places such as city centers, shopping areas, train stations, and university campuses. Although these places are highly visible, the brief parking times and high rotation rates could deliver an inadequate solution for the daily charging needs of users (Giménez-Gaydou *et al.*, 2016). Investors or governments should optimize the locations to reduce investment costs, considering home, parking and workplaces, due to the limited charging facilities, so as to increase the sharing charging level.

A variety of studies have been conducted to examine the location issues of charging stations. For example, Wang and Lin used a mixed integer programming method to measure the benefit of promoting a charging network structure; the case study showed that the use of mixed stations can achieve the optimal deployment for charging stations in the planning area (Wang and Lin, 2013).He and colleagues (2015) applied a genetic-algorithm-based procedure to solve the charging station location problem and found that the proposed bi-level mathematical program can provide insights into the deployment of public charging stations. To solve the 'range anxiety' problem, Kang and colleagues (2015) proposed a cooperative business framework that combines EV manufacturers and CS operators; they found that the integrated decision-making model can assess the profitability of a cooperative business mode. In order to minimize EV drivers' charging trip in charging station, Gao and colleagues (2016) proposed a scheme to manage EV's charging plans, and the scheme considers EV's anticipated charging reservations and parking duration. In their study, Kuby and Lim (2005) suggested a flow-refueling location model (FRLM) to help find optimal charging station locations. To overcome the limitation of FRLM, some improved methods were developed to solve the FRLM, and they showed that the proposed methods outperform those from the previous study (Lim and Kuby,2010;MirHassani and Ebrazi,2012). Similarly, scholars have applied different models in an attempt to find the optimal solution to charging station location problems. These models include a multi-period refueling location model (M-FRLM) (Chung and Kwon, 2015), a multi-period incapacitated hub model (Contreras *et al.*, 2015), and a multi-period service model (Albareda-Sambola *et al.*, 2009). Improved VRPs (vehicle routing problems) model was developed for vehicle last-mile deliveries that addressed the battery power, the improved model can provide great help to charging station location problems (Dorling *et al.*, 2009). These studies provide a basic understanding of what has been done to address the charging station location problem.

By looking deep into these studies, we found that a variety of factors have been considered such as charging accessibility, types of circuits, voltage drawn, circuit load, charging time, electricity price and cost in an effort to solve the charging station location problem (Waraichet al., 2013). Currently, we take these factors as constants (exogenous variables), because they are known for PUEVs. Academics have also examined endogenous variables such as different trips and recharging times for drivers, charging demand, the duration of drivers' activities, the routing of private vehicles, unserved demand and drivers' preferences (Cavadas *et al.*, 2015). However, there is a gap in the literature related to endogenous variables such as demand priority, mileage, EV distribution and passenger distribution, and we notice that any changes to the factors will influence the reusability of the model (Tang *et al.*, 2017). Thus, the model should follow an ecological modeling approach, as this can be used to determine how different policies will affect EV adoption, EV charging, and charging station activity (Adepetu *et al.*, 2016). Thus, we propose an agent-based model that considers demand priority, mileage, EV distribution and passenger distribution in an attempt to find the optimal first stage location plan to improve the sharing charging level.

**TABLE 1. Variables in the charging location model.**

| Variable | Description |
|---|---|
| $X_{max}$ / $Y_{max}$ | Maximum of the charging service scope |
| $X_{min}$ / $Y_{min}$ | Minimum of the charging service scope |
| $TD$ | Vehicle range |
| $LD$ | Remaining mileage |
| $s$ | The number of charging stations |
| $n$ | The number of vehicles |
| $m$ | The demand quantity in one period of time |
| $\lambda$ | Coefficient of routine |
| $g_{ic}$ | Vehicle $i$ charging at station m, $g_{ic}$ =1or 0 |
| $P_j$ | Service priority |
| $X_{ijk}$ | Demand $j$ served by vehicle $i$ at sequence $k$ |
| $y_{ij}$ | Constraints of vehicle-passenger |

## III. THE PROBLEM AND THE MODEL

This study aims to minimize the car moving distances, and car can get charging directly. All EVs move in a linear route. The location sharing problem for the EV charging station is as follows: within a given time, a given number of EV charging stations are randomly assigned in certain areas; it must be determined how to minimize the moving distance for these EVs get charging based on the capacity of the battery, the position of the charging station and, position of the driver, demand point (driver wanted position) and its priority, etc. Limited by mileage, EVs must visit charging stations before the battery runs out. One criterion for being a reasonable shared location is that there is insignificant variance in the access frequencies to different charging stations. The variables are defined as follows for this study (Table 1).

There are two types of vehicle-passenger constraints in the process of reaching the demand point: physical condition and operational condition. These constraints are set as follows:

$$\begin{aligned} \sum_{i=1}^{n} v_i &= V \quad \text{and} \quad \sum_{j=1}^{m} b_j = B \\ idle(v_i) &= V_{idle} \\ type(b_j) &= B_{type} \\ \sum V_{idle} &= \sum B_{type} \\ V_{idle} &= B_{type} \rightarrow service\,(v_i) = b_j \end{aligned} \tag{1}$$

where $v_i$ is the vehicle, $n$ is the number of vehicles, $b_j$ is the demand point, $m$ is the demand point quantity, $V$ is the vehicle set, $B$ is the demand point set, $idle(v_i)$ is the condition of vehicle (returned value is 1,which means vehicle is idle; returned value is 0,which means vehicle is occupied); $V_{idle}$ is the vehicle condition set, $type(b_j)$ is the condition of demand point (returned value ispriority, which considers demand size, demand type, emergency), and $B_{type}$ is the demand type set. Only if the demand point type matches the vehicle type can service start; $service\,(v_i) = b_j$ means that vehicle $i$ provides service for demand point $j$. Constraints is set as follows:

$$A = \begin{matrix} y_{11} & \cdots & y_{1n} \\ \vdots & y_{ij} & \vdots \\ y_{m1} & \cdots & y_{mn} \end{matrix} \tag{2}$$

where $0 < i < n$, $0 < j < m$, $y_{ij} = (0, 1)$.

$$Min\ \lambda(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj})X_{ijk} and Max \lambda \left(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic}\right) X_{ijk} if g_{im} = 1 \tag{6}$$

$$Min\ \lambda(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{i=1}^{n} L_{ij})X_{ijk} if g_{im} = 0 \tag{7}$$

$$\text{subject to } \sum_{i=0}^{n}\sum_{j=0}^{m} X_{ijk} = 1, \quad i = 0, 1, \ldots n \tag{8}$$

$$\sum_{j=0}^{m} X_{ijk} \le 1, \quad j = 0, 1, \ldots m \tag{9}$$

$$X_{ijk} \le y_{ij}, \quad y_{ij} \in \{0, 1\},\ Max(\sum_{j=1}^{m}\sum_{i=1}^{n} L_{ij}) \le TD \tag{10}$$

$$\lambda \left(D_{cj}+L_{ij}\right) \le LD, \quad j = 0, 1, \ldots, m,\ so\ g_{im} = 0 \tag{11}$$

$$\lambda(D_{ic}) \le LD \le \lambda \left(D_{cj}+L_{ij}\right), \quad j = 0, 1, \ldots, m,\ so\ g_{im} = 1 \tag{12}$$

$$\sum g_{i1} \approx \sum g_{i2} \approx \ldots \sum g_{is} \tag{13}$$

$$D_{ic} = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \tag{14}$$

$$D_{cj} = \sqrt{\left(x_c - x_j\right)^2 + \left(y_c - y_j\right)^2} \tag{15}$$

$$L_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{16}$$

The moving distance of the EV is the sum of the distance between the EV and the charging station and the distance between the demand point and the charging stations, that is

$$\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj} \tag{3}$$

To save power, we must choose the shortest moving distance route, that is

$$Min(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj}) \tag{4}$$

Meanwhile, we should make full use of power, that is

$$Max(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic}) \tag{5}$$

Considering $g_{im}$ and $\lambda$, the minimum moving distance of a EV is, (6)–(16), as shown at the top of this page. Equation (8) indicates that each instance of driver demand point is assigned to the car at only one time. Only one demand point can be served by the car at a time (9), and the maximum distance between the demand point and any EV is less than the mileage of the EV (10). If $LD$ is more than the sum of the distance between the demand point and the specific EV and the distance between the demand point and the charging station, the car will go to the demand point (11). If $LD$ is less than the sum of the distance between the demand point and the specific EV and the distance between the demand point and the charging station, while $LD$ is also more than the distance between the EV and the charging station, the car will go to the charging station first (12). (13) means there is no significant difference in charging frequencies. Equation (14) refers to the distance between the EV and charging station $D_{ic}$, where $x_i$, $y_i$ are the coordinates of car $i$; $x_c$, $y_c$ is the coordinates of charging station $c$; and $D_{ic}$ is the distance between EV $i$ and charging station $c$. Similarly, (15) refers to the distance between the demand point and charging station $D_{cj}$, where $x_j$, $y_j$ refers to the coordinate for demand point $j$, and $D_{cj}$ is the distance between demand point $j$ and charging station $c$. Equation (16) is the distance between the EV and demand point $L_{ij}$.

Service can be activated when the demand is high: we call this importance. Service priority should consider the specific situation for a driver: we call this need. There must be a gap between expected service time and actual service time for demand point, which we call emergency. Thus, priority is included in the model:

$$P_j = \theta v_j^{impot} + \beta v_j^{need} + \gamma v_j^{emer} \tag{17}$$

where $\theta$, $\beta$, $\gamma$ are the weight of the factors; and $v_j^{impot}$, $v_j^{need}$ and $v_j^{emer}$ are the factors (demand size, demand type, emergency), respectively. Taking into consideration $P_j$, the minimum moving distance of the EVs is (18) and (19), as shown at the bottom of the next page. We use a linear weighted sum to solve this multi-objective programming problem, that is (20) and (21), as shown at the bottom of the next page, where $\alpha$ is the weight; and values of $\alpha$ refer to the EVs' preference. If $\alpha = 0.15$, it means EV is very liable to choose the shortest distance of total running distance; if $\alpha = 0.95$, it means EV is very liable to choose the shortest distance between charging station and demand point, and so on.

Three different subjects –EVs, charging stations and demand points – are incorporated into the model we proposed above. We text the theoretical foundation and mathematics by Cplex, $L_{ik}$ is the running distance in $k$ time.

$$L_{i,k} = Min(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj}) \tag{22}$$

$\forall i, j, k, c$, if vehicle $i$ get chargingat station $c$:

$$L_{i,k} \ge (X_{i,k,j}+g_{i,k+1,c}-1)D_{jc}+(X_{i,k+1,j'}+g_{i,k+1,c}-1)D_{j'c} \tag{23}$$

If vehicle $i$ has no chargingat station $c$:

$$L_{i,k+1} \geq (X_{j,k,j} + X_{j,k+1,j'} - 1)D_{j'j} \tag{24}$$

The setting of Cplex model is shown in Table 2, and we can get Table 3 by a long time iteration (Mileage is 25.6).

**TABLE 2. Parameters setting for Cplex model.**

| Parameter | Number | Coordinate |
|---|---|---|
| Charging station | 2 | (5.01, 20.55)<br>(40.51, -28.72) |
| Demand | 9 | (-6.04,13.54)<br>(-28.87,-35.33)<br>(49.28,-57.31)<br>(32.2,41.9)<br>(47.39,-56.14)<br>(-46.37,-50.75)<br>(28.86,23.78)<br>(40.61,-1.14)<br>(-39.09,15.04) |
| EV | 2 | (-28.94,25.82)<br>(26.8,-24.07) |

**TABLE 3. Cplex results.**

| Car ID | Rounds | Remaining distance | *Dic* |
|---|---|---|---|
| 1 | 1 | 25.6 | 0 |
| 1 | 2 | 25.6 | 0 |
| 1 | 3 | 24.0030867274645 | 0 |
| 1 | 4 | 12.2208334624901 | 0 |
| 1 | 5 | 10.8633858576081 | 0 |
| 1 | 6 | 8.25448484158763 | 0 |
| 2 | 1 | 25.6 | 0 |
| 2 | 2 | 25.6 | 0 |
| 2 | 3 | 16.0031234247803 | 0 |
| 2 | 4 | 14.0196668459766 | 0 |
| 2 | 5 | 13.2091312206028 | 0 |

Table 3 shows us the rounds of car running, remaining distance of cars and cars' access frequencies (sharing level). It took half an hour to finish the model when considering 2 charging stations, 9 passengers and 2 cars (Table 4); if more agents are included in the model, it will be difficult to calculate the solution. Their relationships are complicated. Any changes to the parameters will influence the reusability of the model. While the Cplex model can provide us one effective way to solve and optimize the mathematical equations.

Thus, we apply simulation model to solve this complex system problem (Maric *et al.*, 2017). We develop three types of agent – charging station agents, EV agents and demand point agents – to analyze the locations sharing of charging stations in the Anylogic platform.

**TABLE 4. Cplex calculating time.**

| |
|---|
| Parallel b&c, 8 threads: |
| Real time = 1615.78 sec. (400239.61 ticks) |
| Sync time (average) = 0.16 sec. |
| Wait time (average) = 0.19 sec. |
| Total (root+branch&cut) = 1616.54 sec. (400484.13 ticks) |

## IV. SIMULATION AND RESULTS

The setting for EVs agent running is shown in Table 5.

**TABLE 5. The setting of EV agent.**

| Item | Symbol | Meaning |
|---|---|---|
| EV Agent | ***o****X*,***o****Y*, | Original of car |
| | *DE* | The moving direction of car |
| | *X* | The horizontal coordinate of car |
| | *Y* | The vertical coordinate of car |
| | *n* | The number of vehicles |
| | *y* | State of car |
| | *TR* | Moving times of car |
| | *LD* | The reminding mileage of car |
| | *TD* | Vehicle range |
| | *CID* | Car ID |

We set the location of the charging station aiming to improve the sharing charging level based on our need; the details are as follows:

$$\text{eCarChargeStation.get(0).setXY}(x_0, y_0)$$

eCarChargeStation.get().setXY() is the function statement; 0is the sequence of charging stations, and x0,y0 are the coordinates of the charging station. Due to the limited mileage, EVs must charge frequently. The layout of the charging stations is considered to be reasonable when the EVs' charging frequencies are not significantly different, which means there is a high level of charging sharing.

Various factors such as the number, coordinates and distance will affect the operation of EVs. In this model, EVs will check for request in a non-stop way. The EV will go to the demand point if it is not occupied. We use a 7-tuple to represent the capability level of EVs, (25) as shown at the bottom of the next page.

$$Min\lambda(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj})X_{ijk}P_j and Max\lambda\left(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic}\right)X_{ijk}P_j if g_{im} = 1 \tag{18}$$

$$Min\lambda(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{i=1}^{n} L_{ij})X_{ijk}P_j if g_{im} = 0 \tag{19}$$

$$Min\lambda\alpha(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{c=1}^{s} D_{cj})X_{ijk}P_j - \lambda(1-\alpha)\left(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic}\right)X_{ijk}P_j if g_{im} = 1 \tag{20}$$

$$Min\lambda\alpha(\sum_{c=1}^{s}\sum_{i=1}^{n} D_{ic} + \sum_{j=1}^{m}\sum_{i=1}^{n} L_{ij})X_{ijk}P_j if g_{im} = 0 \tag{21}$$

Here, $xloc$, $yloc$ are the geographic coordinates, $S_{number}$ is the number of EVs; and $S_{active}$ represents the current state of EVs: when $S_{active} = 1$, the EV is not occupied, otherwise if $S_{active} = 0$, the EV is occupied. $S_{travelDist}$ is the mileage of EVs; $S_{leftDist}$ is the remaining mileagebefore the demand point. $S_{trip}$ represents the running times of some EVs (People can have more needs in one period of time).

The setting for driver agent' demand point is shown in Table 6.

**TABLE 6.** **The setting of demand point agent.**

| Item | Symbol | Meaning |
|---|---|---|
| Passenger Agent | P | Demand priority |
| | PID | Demand ID |
| | RT | The requested arriving time of demand |
| | ST | The actual arriving time of demand |
| | X | The horizontal coordinate of demand point |
| | Y | The vertical coordinate of demand point |

An 8-tuple is used to indicate the attributes of demand point, (26) as shown at the bottom of this page. Here, $xloc$, $yloc$ arethe geographic coordinates of demand point, $P_{number}$ is the number of demand points; $P_{priority}$ is the demand point service priority; $P_{clientID}$ is the demand point ID; $P_{requestingTime}$ is therequired time of arrival; and $P_{servicingTime}$ is the actual arrival time.

The demand point messages from passenger agents are stored in the queue, and the messages are activated according to their "priority". Figure 2 is the full state diagram of the EV agents.

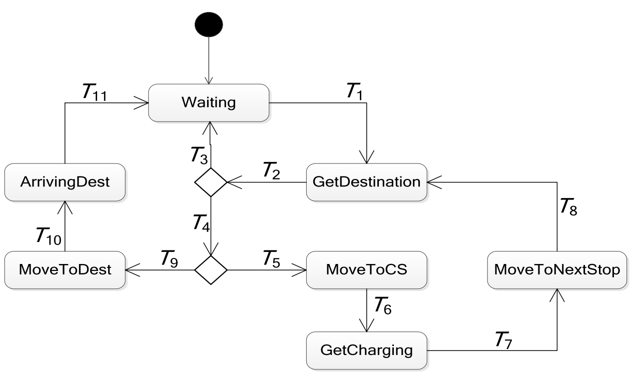



**FIGURE 2.** **State diagram of EV agents.**

This model includes EV agents and demand point agents. Demand point agents will randomly generate new demand due to driver's need and put it into the queue. EV agents will check the queue. When a EV receives a new demand, it will decide to either move to the demand point or move to a charging station.InFigure3, EV starts moving in the "Waiting" state. If the queue is not empty, transition T1 will be fired and a new demand in the queue will be moved out. The EV will enter "GetDestination" state. In this state, $LD$, $D_{ic}$, $D_{cj}$ will be calculated. And then, transition T2will be fired. If $LD < D_{ic}$, EV can't reach the demand point or any charging stations. Transition T3 will be fired and EV will return to "Waiting" state. Otherwise, T4 will be fired. If $LD \geq D_{ic} + D_{cj}$ and $LD > D_{zc}$ (i $\neq$ z), EV can reach demand point directly.T9 will be fired and EV will enter "MoveToDest' state, then transition T10 will be fired and EV will enter "ArrivingDest' state. If battery capacity can't meet the above condition, transition T5 will be fired. EV will find a station for charging, and it will enter "MoveToCS" state for charging. After get fast charging("GetCharging" state), T7 will be fired and EV will enter into "MoveToNextstop" state. In this state, the current location of EV will be set as its new origin. After that, transition T8 is fired, EV will begin its new moving process as before. In this process, we can get the access frequencies for different charging stations, and know the sharing charging level in one period of time.

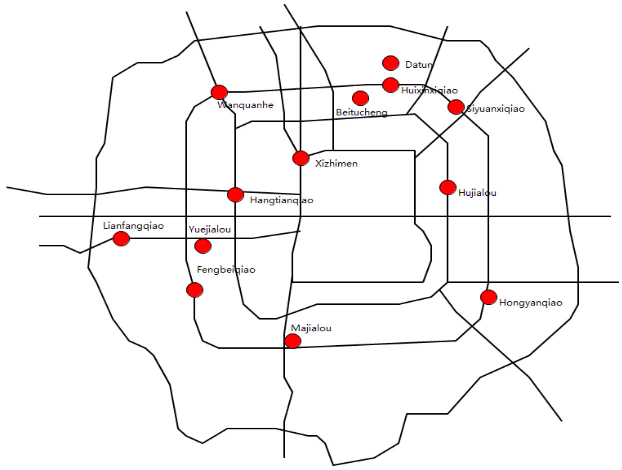



**FIGURE 3.** **Location of charging stations in Beijing.**

For the charging station agent, thirteen charging stations are used for the experimental study, as shown in Figure 4. These stations are located in central areas of Beijing.

Note:

eCarChargeStation.get(0).setXY(-10,182);// coordinate of Datun station

eCarChargeStation.get(1).setXY(-10,210);// coordinate of Huixinxiqiao station

eCarChargeStation.get(2).setXY(-47,228);// coordinate of Beitucheng station

eCarChargeStation.get(3).setXY(-223,224);// coordinate of Wanquanhe station

$$Cap\_sercice\left(xloc, yloc, S_{number}, S_{active}, S_{travelDist}, S_{leftDist}, S_{trip}\right) \tag{25}$$

$$Cap\_sercice\left(xloc, yloc, P_{number}, P_{priority}, P_{clientID}, P_{requestingTime}, P_{servicingTime}\right) \tag{26}$$

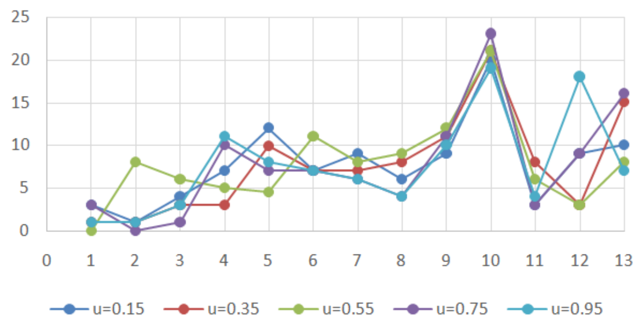



**FIGURE 4. Charging frequencies of charging stations(1).**

eCarChargeStation.get(4).setXY(-120,310);// coordinate of Xizhimen station
eCarChargeStation.get(5).setXY(-200,360);// coordinate of Hangtianqiao station
eCarChargeStation.get(6).setXY(-240,430);// coordinate of Yuejialou station
eCarChargeStation.get(7).setXY(-340,420);// coordinate of Lianfangqiao station
eCarChargeStation.get(8).setXY(-250,490);// coordinate of Fengbeiqiao station
eCarChargeStation.get(9).setXY(-130,560);// coordinate of Majialou station
eCarChargeStation.get(10).setXY(70,240);// coordinate of Siyuanxiqiao station
eCarChargeStation.get(11).setXY(60,350);// coordinate of Hujialou station
eCarChargeStation.get(12).setXY(110,500);// coordinate of Hongyanqiao station

With the location of the charging stations in Beijing, we aim to optimize the existing layout and ensure the high level of charging sharing. The algorithm of searching the optimum is as follows:

(1) getting the value of parameters:

*LD* – The EV's mileages under current power;

*s*–The quantities of charging station;

*n*–The quantities of vehicle;

*m*–The quantities of demand point;

λ–The routine coefficient;

$P_j$–The service priority;

$\alpha$–The weight;

$x_i$, $y_i$ means the original coordinate for car *i*;

$x_c$, $y_c$ means the coordinate for charging station *c*;

$x_j$, $y_j$ means the coordinate for demand point *j*;

$D_{ic}$ is the distance between the car *i*and charging station *c*;

$D_{cj}$ is the distance between the demand point *j* and charging station *c*;

$L_{ij}$ is the distance between the car *i* and demand point *j*.

(2) getting the situations:

*if* $\lambda\left(D_{cj}+L_{ij}\right) \leq LD$, $g_{ic}=0$

*if* $\lambda(D_{ic}) \leq LD \leq \lambda\left(D_{cj}+L_{ij}\right)$, $g_{ic}=1$

*if* $\lambda\,(D_{ic}) > LD$, the car cannot move anywhere.

(3) calculating the minimum of total distance:

CID;//the ID of car
PID;//the ID of demand point
node;//the ID of charging station
if($\lambda(D_{cj}+L_{ij}) \leq LD$)
node=0; // the car can reach the demand point directly
else
double srd; // the shortest running distance for specific car
double s1,s2;// the distance
for(int $i=0$; $i$ <ChargingStation.size();$i++$)
if($\lambda(D_{ic}) \leq LD \leq \lambda(D_{cj}+L_{ij})$)
s1 $= D_{ic}$;
s2 $= D_{cj}$;
if(srd $> \alpha\lambda$(s1 + s2)-(1-$\alpha$) λs1)
td $= \alpha\lambda$ (s1 + s2)-(1-$\alpha$) λs1;
node = i + 1;
if($\lambda(D_{ic}) > LD$) node=-1; // car cannot move anywhere
double Mtd; // the minimum of running distance
Mtd $= \lambda\alpha\{\sum \mathrm{s1} + 0\sum \mathrm{s2}\}$-λ(1-$\alpha$) $\sum$s1

(4) getting the results

The output of model include: the requested arriving time(RST), the actual arriving time(AST), and running distance(RD), the arriving sequence $X_{ijk}$, the charging frequency of charging station(AF). The initial setting of parameters is shown in Table 7.

**TABLE 7. Initial setting of parameters.**

| Parameter | Meaning | Distribution (value) |
|---|---|---|
| *min* X | The minimum horizontal coordinate | -400 |
| *max* X | The maximum horizontal coordinate | 230 |
| *min* Y | The minimum vertical coordinate | 110 |
| *max* Y | The maximum vertical coordinate | 730 |
| *s* | Charging station agents | 13 |
| *m* | Demand agents | 500 |
| *n* | EV agents | 50 |
| TD | Vehicle range | 600 |

Note: The left upper section of the axis is negative, the right lower section of the axis is positive. Simulation time is one year; Map scale is 1:0.046KM, λ=1(exogenous variable).

This paper randomly generates500 demand point information (coordinate, priority, service time),50 EVs information (coordinate, state),and 13charging stations information (coordinate). The results are shown in Table 8 by100 iterated times.

We can find that the first vehicle arrived at 12 different demand points, such as 42, 50,56, 92, and total running distance is 2515.79;The second vehicle arrived at 13 different demand points, such as 6, 52, 83, 18, 80, and total running distance is 2729.43;The third vehicle arrived at 7 different demand points, such as 93, 88, 96, 58, and total running distance is 1844.89;The fourth vehicle arrived at 11 different demand points, such as 1, 48, 33, 28, 3, 89, and total running distance is 2478.67;The fifth vehicle arrived at 10 different demand points, such as 29, 86, 45, 90, and total running distance is 1671.80;The sixth vehicle arrived at 8 different demand points, such as 94, 79, 12, 40, and total running distance is 1895.91. Next, we will calculate the charging

**TABLE 8.** Part of the simulation results.

| OCC(x) | OCC(y) | CP(x) | CP(y) | CSI | LD | RT | ST | PID | P | CID | RD |
|---|---|---|---|---|---|---|---|---|---|---|---|
| -240 | 430 | -387 | 485 | 0 | 600 | 20 | 24 | 42 | 0.99 | 1 | 157 |
| -387 | 485 | -122 | 243 | 0 | 443 | 20 | 26 | 50 | 0.78 | 1 | 359 |
| -120 | 310 | -223 | 578 | 0 | 600 | 20 | 32. | 56 | 0.701 | 1 | 287 |
| -130 | 560 | -35 | 497 | 0 | 600 | 20 | 34 | 92 | 0.57 | 1 | 114 |
| 183 | 473 | -89 | 390 | 0 | 600 | 20 | 21 | 6 | 0.97 | 2 | 285 |
| -223 | 224 | -312 | 241 | 0 | 600 | 20 | 24 | 52 | 0.90 | 2 | 91 |
| 411 | 451 | -81 | 272 | 0 | 600 | 20 | 22 | 93 | 0.96 | 3 | 524 |
| -200 | 360 | 87 | 673 | 0 | 600 | 20 | 53 | 34 | 0.02 | 4 | 425 |
| 54 | 134 | 166 | 290 | 0 | 600 | 20 | 21 | 29 | 0.96 | 5 | 192 |
| 80 | 63 | 170 | 257 | 0 | 600 | 20 | 23 | 94 | 0.96 | 6 | 213 |

Note: OCC: the original coordinates of the EV, CP: the coordinates of the demand, CSI: charging station ID,LD: the remaining mileage, RT is set as 20 simulation time for all demand, ST is the time when passengers receive the service, PID: demand ID, P: demand priority, CID:car ID,RD: the running distance of car,0 means no need to charge in CSI.

frequencies for different charging station, so as to know the sharing charging level.

## V. DISCUSSION AND OPTIMIZATION OF THE LAYOUT

We applied Anylogic to analyze the charging frequency to know sharing level for the location of charging stations. At first, we will determine the main factors influencing the location of charging stations. In the first and second situations, priority is taken into consideration or not, respectively. The results for charging frequencies are shown in Table 9.

**TABLE 9.** Situations 1 & 2–priority is considered or not considered.

| | | | | |
|---|---|---|---|---|
| CS5 | α=0.15 | ARCF（%） | Priority is considered | 40.5 |
| | | | Priority is not considered | 37.5 |
| | α=0.35 | ARCF（%） | Priority is considered | 41.5 |
| | | | Priority is not considered | 34.5 |
| | α=0.55 | ARCF（%） | Priority is considered | 43.5 |
| | | | Priority is not considered | 33.5 |
| | α=0.75 | ARCF（%） | Priority is considered | 47.5 |
| | | | Priority is not considered | 44.5 |
| | α=0.95 | ARCF（%） | Priority is considered | 50 |
| | | | Priority is not considered | 39.5 |

CS: charging station; ARCF: accumulated ratio of charging frequency

Differences exist in the charging frequencies between Situation 1 and 2 as shown in Table 9. Thus, priority significantly affects the location of EV charging stations.

In addition, we applied ANOVA(Analysis of Variance) to analyze the charging frequencies for Situation 3 (changing mileage for charging station), Situation 4 (changing EV distribution and number) and Situation 5 (changing demand point distribution and number).Similarly, the results indicate that mileage, EV distribution and number, demand point distribution and number, are the main factors affecting the sharing charging level of EV charging stations (these factors are also considered in the charging location model). In the following section, we only optimize the layout for one situation: Mileage is 600, priority is considered, and EVs and passengers have the same distribution. We set the parameters as in Table 10.

**TABLE 10.** Parameter settings.

| Agent | Parameter | Meaning | Distribution (value) |
|---|---|---|---|
| Demand | X | The horizontal coordinate of agent | U(minX,maxX) |
| | Y | The vertical coordinate of agent | U(minY,maxY) |
| EVs | X | The horizontal coordinate of agent | U(minX,maxX) |
| | Y | The vertical coordinate of agent | U(minY,maxY) |

We set the simulation period to one year. To reflect people's preferences, $\alpha$ is set as0.15,0.35,0.55,0.75,0.95 respectively. A summary of the charging frequencies is shown in Figure7.

The results indicate that whatever $\alpha$ is, the charging frequencies of charging stations 4,5,6,9,10,12,and 13 are high, while those of charging stations 1,2,3,7,8,11 are relatively low. This indicates that the existing locations of charging stations are not appropriate in Beijing, that also means the sharing charging level is low. We need to improve the usage of charging stations 1,2,3,7,8, and 11.The optimization methods used here include adding options at the edge point and reducing the density of the charging station layout. Optimization will end when there is no significant difference in charging frequencies, that is $\sum g_{i1} \approx \sum g_{i2} \approx \ldots \sum g_{is}$, while maintaining the minimum number of charging stations $min(s)$.

According to the location of Lianfangqiao station, Yuanjialou station, Fengbeiqiao station and Majialou station, we select point A $(-400,420)$, point B $(-400,730)$ and point C $(-130, 730)$ to calculate the center of gravity, which would be the added charging station. We used genetic algorithms and a Monte Carlo simulation to obtain the coordinates $(-265,575)$ of the new charging station (ID 14). As indicated in Figure8-a, the charging frequencies of charging stations 5,10,12,13, and 14 are relatively high (over 10%), while those

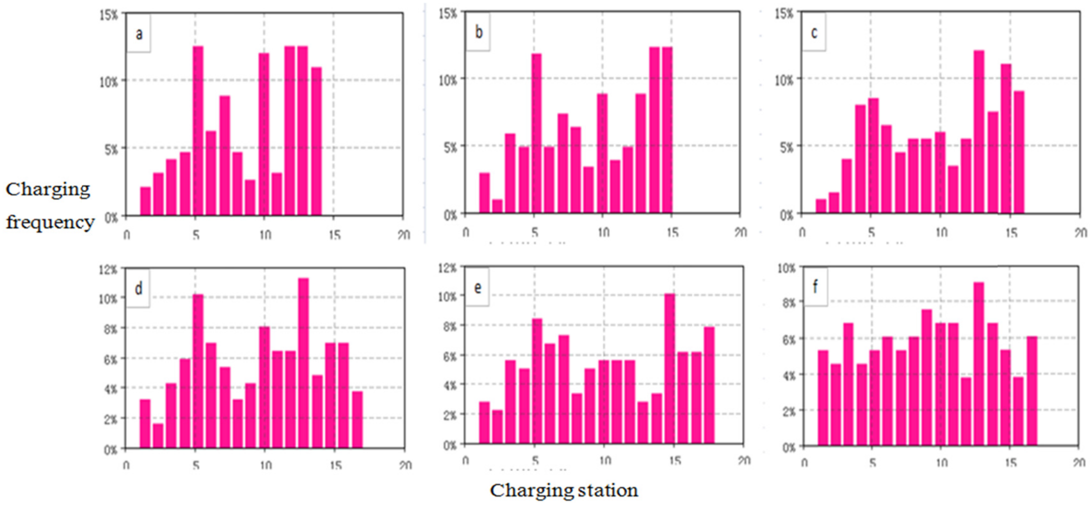
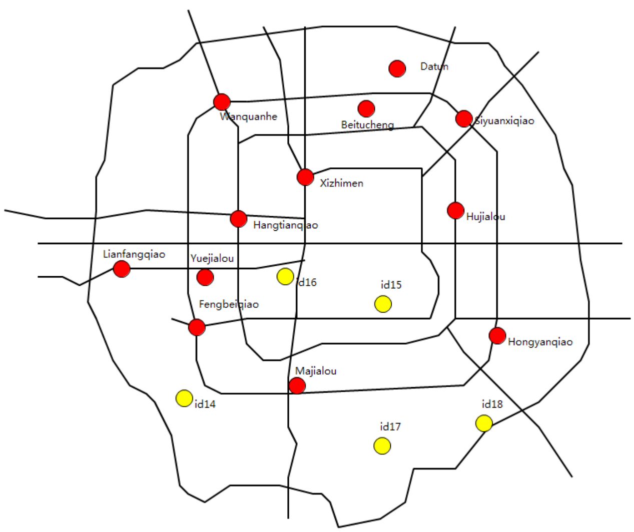



**FIGURE 5.** **The charging frequency for the charging stations(2).**




**Legends:** **Original charging stations**, **Added charging stations.**

**FIGURE 6.** **Optimized locations of the charging stations.**

of charging stations 1,2,3,4,8,9, and 11 are relatively low (less than 5%). The same types of methods are developed to illustrate the optimization (Figure8-b,c,d,e).It is concluded that $\sum g_{i1} \neq \sum g_{i2} \neq \ldots \sum g_{is}$.

As discussed above, it is found that the charging frequency of Huixinxiqiao station is low. Thus, we illustrate optimization without Huixinxiqiao station. As indicated by Figure8-f, the charging frequencies of the selected charging stations maintain a level of 4% to 7%, which is relatively even. It is concluded that $\sum g_{i1} \approx \sum g_{i2} \approx \ldots \sum g_{is}$. The locations of the charging stations tend to be more reasonable, the sharing charging level is improved. The optimized location of the charging stations is shown in Figure 9.

There is weak demand to locate charging stations in areas of low charging frequency, while there is strong demand to locate charging stations in areas of high charging frequency. Eventually, we can obtain the coordinates of all charging stations: Datun station (−10,182), Beitucheng station (−47,228), Wanquanhe station (−223,224), Xizhimen station (−120,310), Hangtianqiao station (−200,360), Yuejialou station (−240,430), Lianfangqiao station (−340,420), Fengbeiqiao station (−250,490), Majialou station (−130,560), Siyuanxiqiao station (70,240), Hujialou station (60,350), Hongyanqiao station (110,500), station ID 14 (−265,575), station ID 15 (−27,462), station ID 16 (−144,429), station ID 17 (−28,632), and station ID 18(94,605).

## VI. CONCLUSION

The factors related to the sharing charging of PUEVs are complicated and context specific. We fill the gap in literature by adopting reasonable location. We focus on demand point priority, mileage, PUEV distribution and demand point distribution in this study. An NP model and agent-based model are developed to analyze the charging frequencies and sharing charging level for the charging stations. Through a case study of Beijing, we discuss the model in five situations. Optimization methods are used in this paper, such as adding options at the edge point, lowering the density of the charging stations' layout, obtaining three vertices of the biggest triangle, calculating the shortest distance from the reference point, and deleting unreasonable points, to analyze the existing layout.

In this paper, an optimization problem is defined for addressing the location problem of EVs charging stations to improve the sharing charging level. The contributions of the paper are as follows:

(1) Other researches considered battery size, charging capacity, charging power and battery swapping which are exogenous variables. We focus on demand point priority, mileage, PUEV distribution and demand point distribution which are endogenous variables.

(2) One criterion for being a reasonable location is that there is insignificant variance in the access frequencies to different charging stations, which is different from prior studies.

(3) An NP model and agent-based model are developed to analyze the charging frequencies for the charging stations. Through a case study of Beijing, we discuss the model in five situations. The proposed model can be used for EV charging stations' location in densely populated metropolis.

Of course, we have limitations in our paper, such as, assume a short charging time, thirteen charging stations are used for the experimental study. We will consider more practical constraints in our future research.

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