Article:

Wang, Y, Zhao, Y, Gan, S et al. (3 more authors) (2023) Optimization of Charging Stations Integrated with Dynamic Transportation Systems in Metropolises. Transportation Research Part D: Transport and Environment, 119. 103726. ISSN 1361-9209

https://doi.org/10.1016/j.trd.2023.103726

Optimization of Charging Stations Integrated with Dynamic Transportation Systems in Metropolises

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Abstract

The development of electric vehicles (EVs) is expected to play an important role in achieving the emission reduction targets in the transportation sector by many countries and regions, including China's dual carbon goals. A bottleneck to the mass roll-out of EVs is the limited charging facilities. This paper considers the planning of charging facilities for a new developing area in a metropolis, and an optimization model for charging station planning based on the dynamic transportation system is proposed. The proposed model is developed using an objective framework that considers the spatio-temporal characteristics of EV charging demand in order to minimize the overall cost while the constraints from suppliers and drivers are met. The Voronoi diagram is used to determine the final service boundary of each charging station, and the effect is verified in the planning of charge stations for the Yizhuang new town in Beijing. The case study confirms that the proposed method can optimise the charging facilities that fit well with the traffic network conditions. Furthermore, it is shown that the charging demand varies in accordance with the population density and regional functionality in different areas.

Keywords: charging station, optimization, dynamic traffic system, metropolis

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1. Introduction

To address the climate change challenge and the issues of sever emissions from substantive consumption of fossil fuels in all sectors, many governments have committed to reducing greenhouse gas emissions, and around 140 countries and regions worldwide have committed or considered achieving net zero by the middle or second half of this century. For example, the Chinese government has proposed a number of measures to achieve the 'dual carbon' goal, and the rapid roll-out of electric vehicles (EVs) is considered a crucial measure for decreasing carbon emissions (IEA, 2021).

Accordingly, the development of charging facilities has a considerable application potential, and both governments and energy-related business sectors have placed great importance on the development of charging stations (Fathabadi, 2020a). The planning and design of charging stations is a complex process and a number of questions need to be answered, for example: how many and where should charging stations should be located in the planning area; what is the capacity for each charging station, etc (Lee and Han, 2017). In other words, charging station planning is an optimization problem in which the quantity, locations, and capacities of charging stations should all be determined, while the objective function includes investment costs such as construction costs, operation costs, and EV user travel costs (including power and time), and the constraints include power grid safety and EV drivers' requirements (Zhao et al., 2020; Cui et al., 2019).

The construction of charging stations would have a big impact on the power grid network and traffic system (Umoren et al., 2020; Seyedyazdi et al., 2020). Improper charging station location may lead to traffic congestion and inconvenience to EV users, and further jeopardize the power grid's stability and safety (Mao et al., 2019; Xiong et al., 2017). Consequently, there has been much effort reported on charging station optimization in recent years (Feng et al., 2020). For example, some studies focus on the service provision of charging infrastructure, primarily considering the uncertainties and complexities posed by EV drivers and traffic conditions. In (Faridimehr et al., 2018), a two-stage stochastic programming methodology is proposed in to arrange publicly accessible charging stations while maximizing EV drivers' convenience. The arrival and dwelling times, the battery states, the drivers' charging willingness, and the number of EVs in the community have all been taken into account in this model. The scheduling of EV charging is based on the overall optimization of the traffic system, including driving demands and road speed, which provides convenience to EV drivers while making charging or battery swap decisions (Luo et al., 2020). A novel planning method for fast charging facilities that takes into account numerous factors in the system is presented to achieve the optimization of the objective to satisfy the demands of EVs, drivers, and traffic systems while meeting the constraints for power grid safety (Kong et al., 2019). In conclusion, these studies mainly analyse the behavior of EV users in the traffic network, revealing the potential barriers in meeting consumers' charging requirements and optimizing the charging facilities while satisfying the constraints of the power system.

On the other hand, the coupling effects of the charging stations and traffic system have also been researched, where the temporal-spatial charging demand is considered (Koufakis et al., 2019; Jia et al., 2018; Jeon et al., 2021; Guo et al., 2018). In (Dong et al., 2016), a spatial and temporal model is formulated to find the EV charging points on the round freeway, and the battery characteristics and transportation behaviors are simulated using the Monte Carlo method. An incentive-based demand response program, which combines both the investment cost and demand response cost in the objective function, is developed and solved using the particle swarm optimization method to overcome the complexity introduced by the high EV penetration in the network (Simorgh et al., 2018). The GAMS solver is used to deal with a comprehensive planning model to identify the optimal expansion strategy, in which the steady-state distribution of traffic flows and driving range limited by battery capacity are considered (Wang et al., 2018). The fast-charging station deployment problem is solved by considering the elastic charging demand which combines the driving distance and waiting time with the probability functions (Poisson-distribution and exponential distribution) (Gan et al., 2020). To handle single charging events in the highway traffic system, a model based on actual demand profiles is introduced, in which the temporal traffic pattern is obtained from a comprehensive datasets of individual car trips (Pesch et al., 2020). The travel and charging patterns for minimizing the EVs' cost in a system which is equipped with fast charging stations are investigated, and various factors are considered, such as how the supplier influences drivers' charging behavior and how the drivers' decision affects station congestion and charging load (Moradipari et al., 2020; Falchetta, 2021). A four-step method to deploy normal and fast charging stations is proposed, which estimates the charging demand distribution based on traffic statistics. (Wang et al., 2019b)

In summary, most existing research has focused on EV users' satisfaction levels, such as the queuing time, the travel time and power needed, or the charging duration, etc. (Wang et al., 2021); while some other studies have investigated the charging utilization based on the pricing mechanism or the profit maximization (Zhang et al., 2018; Moradipari and Alizadeh, 2019). The research on highway traffic, fast-charging stations and steady-state traffic networks can be found in (Kchaou-Boujelben, 2021; Funke et al., 2019). Furthermore, some studies on the layout of charging stations based on the charging demand for the freeway or other countries are also reported, in which the charging demand is formulated by statistic simulation methods (Yang et al., 2018; Wang et al., 2019a). However, little has been done in the literature to examine the effects of temporal and spatial charging demand, in other words, the dynamics of traffic systems as well as the power grid's constraints in a metropolis.

This article aims to bridge the aforementioned gap and investigate the charging station planning based on the traveling and charging characteristics of EVs at different time periods for a new development area of a metropolis. Firstly, the dynamics of the traffic network need to be modelled based on the information of network topology, traffic flow, and road impedance. Secondly, the spatio-temporal pattern of EV charging demand will be investigated by studying the probability distribution of EV mileage and the charging probability of EVs, in an attempt to provide a rational basis for deciding the location and scale of charging stations. Thirdly, taking the charging demand in the planning region as a preliminary, the charging station optimization model is constructed, with the aim of minimizing the overall supplier and driver costs. Finally, the charging station strategy is improved and implemented by using the Voronoi diagram. For designing the charging stations in the Yizhuang new town in Beijing, the quantity, capacity, and locations of charging stations are optimized while considering the limitations and constraints from both the traffic system dynamics and the power network. Furthermore, the impact of EV charging load with various EVs penetration rates in the planning system is investigated .

2. Problem formulation

2.1. The traffic network model

The traffic network model, which includes the topology of the road network and the formulation of traffic flow, is detailed below. A weighted directed graph, based on the graph theory analysis, establishes the topology of the road network. The schematic diagram of a traffic network system is shown in Fig. (1).

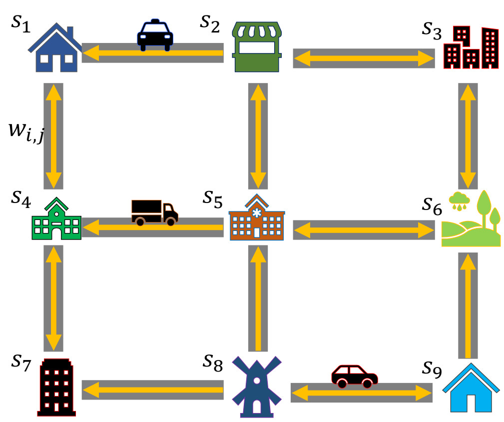


Figure 1: The traffic network system

The position of each road intersection is expressed by its longitude and latitude, and the distance matrix between traffic intersections is computed as follows:

$$\begin{cases} \mathrm{Net} = \{\mathrm{S}, \mathrm{W}, \mathrm{T}\} \\ S = \{s_i | i = 1, 2, ..., n\} \\ W = \{w_{i,j} | i = 1, 2, ..., n, j = 1, 2, ..., n\} \\ T = \{t | t = 0, 1, ..., 24\} \end{cases} \tag{1}$$

where Net denotes the traffic network system; S represents the set of intersections; n is the number of intersections; W indicates the road impedance matrix from intersection i to intersection j; and T defines the set of time slots, which divides a day into 24 hours according to the references (Tehrani, 2015; Liu et al., 2021; Pal et al., 2021).

Suppose that there exist two intersections which are related to each other, indexed by i and j. The traffic flow between the two intersections can be measured with the multi-parameter gravity model (Erlander and Stewart, 1990):

$$V_{i,j}^t = C \frac{N_i^\alpha N_j^\gamma}{W_{i,j}^t} \tag{2}$$

where $V_{i,j}^t$ can be represented as the traffic flow between the two intersections at time period t. C is the proportional coefficient; N_i and N_j are the 'mass', which can be reflected as the population sizes of areas with R as the radius centered on points i and j respectively; α and γ are the application factors that alter the population dependency. $W_{i,j}^t$ stands for the function of road impedance:

$$W_{i,j}^t = a_0 z_t^b + \sum_k a_k \cdot x_k \tag{3}$$

where x_k represent the factors that influence road impedance, such as minimum velocity, number of traffic lanes, density of bus stops and signalized intersections, number of non-motor vehicles, and so on. a_0, a_k and b are the estimated impact factor parameters; z_t denotes the road saturation level, which is related to the time period t.

2.2. The EVs charging demand model

Because of mobility, the charging demand of EVs varies with time, which is dependent on the factors such as driving mileage, state of charge and EV drivers' charging willingness. We aim to fulfil the travelling requirements of EVs in the charging demand model, which is complicated due to the large number of EVs, variety of travel mileages, and various states of charge (SOC) when drivers decide to charge (for example: some people intend to charge when SOC is 20% while some people prefer to charge when SOC is 10%). In this section, the EV charging demand will be modeled based on the statistic of the whole traffic system.

(1) For EVs, the driving mileage per hour varies during the day. Therefore, the percentage of mileage per hour over the total daily mileage is variable, and its probability density curve can be described by a mixed Gaussian function (FHWA, 2017; Calearo et al., 2021):

$$f_s(x) = \sum_{k=1}^{K} \pi_k \cdot e^{-(\frac{x-\mu_k}{\sigma_k})^2} \tag{4}$$

where π_k means the weight of the k-th Gaussian model and $\sum_{k=1}^{K} \pi_k = 1$; μ_k and σ_k are the mean and variance values of k-th Gaussian model. The driving mileage at time t would be:

$$L(t) = L_0 \cdot \int_0^t f_s(x)dx = L_0 \cdot F_s(t) \tag{5}$$

where L_0 stands for the daily driving mileage.

(2) Suppose the initial SOC of an EV is β_0, thus the relationship between the SOC of the EV's battery and its driving mileage $L(t)$ at time t can be expressed as:

$$SOC_t = \beta_0 - \frac{L(t)}{l_{max}} \tag{6}$$

where l_{max} is the maximum range of EVs when they are fully charged.

(3) The SOC of EVs when drivers are willing to charge could be formulated as a Weibull distribution, with the following probability density function

(Fathabadi, 2020b):

$$f_{SOC}(x) = a \cdot b \cdot x^{b-1} \cdot e^{-ax^b} \tag{7}$$

where a and b are parameters of the Weibull distribution; suppose the SOC of EV is β $(0 < \beta < 1)$, and then the probability driver go to charge is:

$$F_{soc}(\beta) = \int_0^{\beta} f_{SOC}(x)dx \tag{8}$$

(4) The probability of charging for an EV on the road at time t is:

$$P_{charg} = \int_0^{SOC_t} f_{SOC}(x)\,dx = \int_0^{\beta_0 - \frac{L(t)}{l_{max}}} f_{SOC}(x)\,dx \tag{9}$$

(5)The number of EVs that need to charge at a specific intersection i at time t is given as:

$$N_i^t = V_i^t \cdot \alpha \cdot P_{charg} \tag{10}$$

where $V_i^t = \sum_j V_{i,j}^t$ is the real-time traffic flow of intersection i at time t based on equation (2), avoiding double counting when calculating V_j^t. α stands for the penetration level of EVs on the road.

(6) Assume there are I intersections in the planning area, the total number of EVs to be charged in one day is formulated as:

$$\Xi = \sum_{i=1}^{I} \sum_{t=1}^{24} N_i^t \tag{11}$$

Based on the aforementioned definitions, instead of using the static demand model based on the conventional location theory (Williams, 1997), the objective of optimizing charging facilities can be formulated to meet the time-varying charging requirement in the traffic system. A key feature of this optimization model is that it can incorporate the dynamic distribution of charging demand based on the traffic flow to better suit the convenience of EV drivers.

3. Optimization model for charging stations

The aim of this optimization approach is to design the specifics (such as the quantity, capacity, and locations) of new charging stations in a given planning area subject to corresponding traffic and power network constraints. The objective function has two parts: the construction costs and the users' travel costs.

$$\min \mathrm{C} = \sum_{\mathrm{k}=1}^{\mathrm{K}} (\gamma_1 \mathrm{C}_{\mathrm{k}}^1 + \gamma_2 \mathrm{C}_{\mathrm{k}}^2) \tag{12}$$

where C_k^1 denotes the annual investment cost of charging station k; C_k^2 represents the travel cost when users go to charging station k; γ_1 and γ_2 are the weighted parameters. The decision-makers can adjust the coefficients γ_1 and γ_2 to reflect the relationship between investment and drivers' costs. In this article, γ_1 and γ_2 are equal to 1, representing a balanced approach (Zhang et al., 2015; Huang and Kockelman, 2020).

3.1. The annual investment cost

The investment cost C_k^1 contains the cost of construction, operation and maintenance, and loss of electricity each year:

$$C_k^1 = C_{build} + C_{mtn} + C_{loss} \tag{13}$$

(1) The construction cost C_{build} for the charging station k mainly includes equipment purchase cost, land rent and civil construction cost:

$$\begin{aligned} C_{build} =& \frac{r_0(1+r_0)^{n_0}}{(1+r_0)^{n_0}-1}(N_k c_{charg} + S_k c_{trans} \\ &+ A_k c_{field} + A_k c_{roof} + L_k c_{line} + C_h) \end{aligned} \tag{14}$$

where r_0 denotes the rate of discount; n_0 indicates the life span of the charging station; N_k is the number of available piles in station k; c_{charg} represents the price per charging pile ($); S_k means the capacity of transformer in station k (KW); c_{trans} is the price of unite capacity for the transformer $(\$/KW)$; A_k is the area size of station k (m^2); c_{field} and c_{roof} are the rent cost and shed cost per unit area respectively $(\$/m^2)$; L_k is the transmission line length from station k to the power distribution system (m); c_{line} stands for the price of per unite line $(\$/m)$; C_{hk} is the cost of civil engineering for charging station k ($).

(2) The operating and maintenance cost C_{mtn} for charging station k consists of the labour cost and the maintenance cost of equipment:

$$C_{mtn} = \gamma C_{build} \tag{15}$$

where γ is the proportion of labor and maintenance cost to the construction cost C_{build} for a charging station, which is usually set to be 9%.

(3) For the charging stations, the loss cost C_{loss} mainly considers line loss, charging loss and transformer loss. The line loss refers to the power loss on the cable line from the charging pile to the electricity metering point, which is related to the length, the cross-sectional area of the cable and the temperature. The charging loss means the power consumed by the charging pile when maintaining the operation of components in the standby state. The transformer loss includes open-circuit loss and load loss of the transformer.

$$\begin{aligned} C_{loss} &= (P_{line} + P_{charg} + P_{trans})T_c P_c \\ &= (p_l \cdot l_{cap} + p_c \cdot c_{cap} + p_t \cdot t_{cap})T_c P_c \end{aligned} \tag{16}$$

where $P_{line}, P_{charg}, P_{trans}$ are the line loss, charging loss and transformer loss per year respectively (kw), which could be calculated based on the loss rates (p_l, p_c and p_t) and capacities (l_{cap}, c_{cap} and t_{cap}) of line transmission, charging piles and transformers; T_c means the annual working time (h); P_c is the electricity price ($\$/kwh$).

3.2. The annual travel cost

Since the distances between current locations and different stations are time-varying, the arrangement of charging facilities in the planning area will have a big influence on the travel cost of customers. In this section, the travel cost C_k^2 can be split into the power cost and driving time from the current position to charging station k, as well as the queuing time at station k.

$$C_k^2 = C_{kp} + C_{km} \tag{17}$$

(1) The electrical energy cost for users C_{kp} is calculated by the distance from intersection i to charging station k:

$$C_{kp} = \sum_t \sum_i \frac{d_{i,k} \cdot N_i^t}{l_0} \cdot P_c \tag{18}$$

(2) The time cost for users C_{km} includes the traveling time from current location to charging station k and queuing time at charging station k:

$$C_{km} = \left[\sum_t \sum_i \frac{d_{i,k} \cdot N_i^t}{v_{i,k}^t} + \sum_t W_k^t \right] \cdot c_{time} \tag{19}$$

where $d_{i,k}$ denotes the driving distance from the intersection i to charging station k (km); N_i^t indicates the number of EVs which need to be charged at traffic intersection i; $v_{i,k}^t$ indicates the driving speed (km/h); l_0 is the mileage per unit electrical energy (km/kwh); c_{time} is the cost of time for drivers in the planning area($\$/h$); P_c is the electricity price($\$/kwh$).

In this paper, we assume that there are two types of charging piles in the charging stations, namely fast charging piles and slow charging piles. We consider the 'first come first serve' policy for EV charging. Based on the Markov transition process and dynamic M/M/C queuing model (Vahdani et al., 2012; Moghaddam et al., 2018), the queuing time at time period t in charging station k could be calculated as:

$$W_k^t = W_{k,f}^t + W_{k,s}^t \tag{20}$$

where $W_{k,f}^t$ is the queuing time if users choose fast charging at charging station k in the time period t:

$$\begin{cases} W_{k,f}^t = \frac{P_{0,f}}{(N_{k,f}-1)!} \cdot (\frac{\lambda_{f,t}}{\mu_{f,t}})^{N_{k,f}} \cdot \frac{\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}} \\ P_{0,f} = \left[\sum_{n=0}^{N_{k,f}-1} \frac{1}{n!} \cdot (\frac{\lambda_{f,t}}{\mu_{f,t}})^n + \frac{1}{N_{k,f}!} (\frac{\lambda_{f,t}}{\mu_{f,t}})^{N_{k,f}} \cdot (\frac{N_{k,f}\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}}) \right]^{-1} \end{cases} \tag{21}$$

and $W_{k,s}^t$ is the queuing time if users choose slow charging at charging station

k in the time period t:

$$\begin{cases} W_{k,s}^t = \frac{P_{0,s}}{(N_{k,s}-1)!} \cdot (\frac{\lambda_{s,t}}{\mu_{s,t}})^{N_{k,s}} \cdot \frac{\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}} \\ P_{0,s} = \left[\sum_{n=0}^{N_{k,s}-1} \frac{1}{n!} \cdot (\frac{\lambda_{s,t}}{\mu_{s,t}})^n + \frac{1}{N_{k,s}!}(\frac{\lambda_{s,t}}{\mu_{s,t}})^{N_{k,s}} \cdot (\frac{N_{k,s}\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}})\right]^{-1} \end{cases} \tag{22}$$

where $\lambda_{f,t} = N_k^t \cdot \alpha$ and $\lambda_{s,t} = N_k^t \cdot (1-\alpha)$ are the number of EVs for fast charging and slow charging at time period t respectively; α means the probability of an EV choosing fast charging, which varies with time, bigger in the daytime and smaller at night. $N_{k,f}$ and $N_{k,s}$ are the numbers of fast charging piles and slow charging piles in station k respectively. The charging rates of fast and slow charging piles at time period t are $\mu_{f,t} = \sum_{i=1}^{\lambda_{f,t}}(1 - SOC_i) \cdot TD_f$ and $\mu_{s,t} = \sum_{i=1}^{\lambda_{s,t}}(1 - SOC_i) \cdot TD_s$ respectively; TD_f and TD_s are the maximum service time of fast charging and slow charging respectively if the SOC of an EV is zero.

The flowchart of the proposed optimization algorithm is shown in Fig. (2).

3.3. Constraint conditions

The design of charging stations should consider the constraints imposed by customer demand, the structure of the road network, and the power network. These limitations are imposed to ensure that 1) the queuing time for customers does not exceed the threshold during peak hours; 2) the grid node capacity does not exceed the limit when the charging station is connected; 3) the system safety criteria are met, etc.

3.3.1. Customer constraints

(1) Queuing time constraint for EV drivers

$$q(t) \leq q_{max} \tag{23}$$

where $q(t)$ denotes the queuing time at time period t for drivers; q_{max} represents the maximum allowable queuing time for EVs.

(2) Distance constraint for EVs

$$min(l_{ik}) \leq l_{max} \tag{24}$$

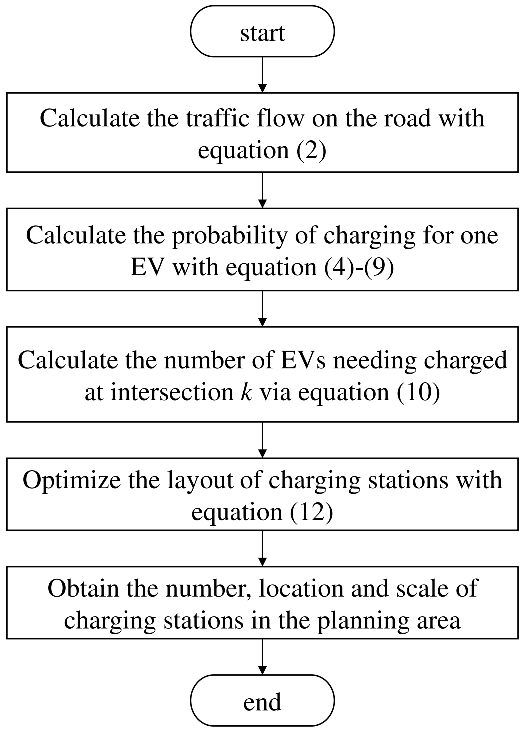


Figure 2: The flowchart of the proposed algorithm

where l_{ik} indicates the distance from traffic intersection i to charging station k; l_{max} is the maximum driving distance of EVs when they go to charge. According to the relevant policy in Beijing, EVs could get charged within $5km$ in the sixth ring.

3.3.2. Charging station constraints

(3) Capacity constraint for charging stations

$$\sum_{k=1}^{K} s_{kr,max} \leq S_{r,max} \tag{25}$$

where K is the quantity of charging stations connected to the power grid node r; For the power grid node r, $s_{kr,max}$ means the maximal scale of charging station k; $S_{r,max}$ indicates the maximum allowable capacity added to the power grid node r, which mainly depends on the load rate and line transmission capacity.

(4) Distance constraint between charging stations

$$d_{jk} \geq d_{min} \tag{26}$$

If d_{jk}, which represents the distance between two charging stations j and k, is too small, there would be a high vacancy rate for charging piles, resulting in the waste of resources. Therefore, the distance between two charging stations is generally larger than the minimum distance d_{min}. At the end of the 14th Five Year Plan in China, EVs could find public charging facilities within $1km$ in the core area of Beijing.

3.3.3. Power system constraints

The charging stations would bring security and stability issues when they are connected to the power system (Yang et al., 2015). Thus, there are some constraints which should be considered, such as capacity and voltage limitations. In detail, the capacity of the grid node does not exceed the maximum power supply and the voltage of each grid node should be within the safety range when charging stations are connected to the power system.

(5) Capacity constraint for power grid

$$\sum_{i=1}^{N} s_{i,max} + s_0 \leq (1 - \varepsilon) \cdot S_{max} \tag{27}$$

where N denotes the number of charging stations in the planning area; $s_{i,max}$ is the maximal size of charging station i; s_0 means the initial load capacity of the power system before linked to the charging stations; ε represents the margin of power system, which is normally 5%; S_{max} is the maximum power supply capacity of the power system in the planning area.

(6) Voltage constraint for power nodes

$$\alpha_{lower} \cdot U_{0,r} \leq U_r \leq \alpha_{upper} \cdot U_{0,r} \tag{28}$$

where α_{lower} and α_{upper} are the lower and upper limit rates respectively; $U_{0,r}$ is the rated voltage of grid node r; U_r is the voltage after the charging station connected to power node r.

3.4. Voronoi diagram

Once the charging stations have been planned, the corresponding service boundary of each charging station can be obtained by Voronoi diagram, which is also known as Tyson polygon graph (Aurenhammer, 1991; Boots et al., 2009). The Voronoi diagram divides the planning area into N polygon regions centered on points $p_i (i = 1, 2, \cdots, N)$. As shown in Fig. 3, the boundary line between the polygon areas formed by two adjacent points is bisected and perpendicular to the line between these two points. There is a proximity principle for the points: the distance $d(x, p_j)$ from any point $x(x \in R(p_i))$ to the center point $p_j (j \neq i)$ of other areas is bigger than the distance $d(x, p_i)$ from the point x to the center point p_i of the current area. Therefore, each point in the Voronoi diagram has a stronger relationship with the region to which it belongs. For the points $p_i (i = 1, 2, \cdots, N)$, the service boundary $R(p_i)$ can be determined as follows:

$$R(p_i) = \{d(x, p_i) < d(x, p_j)\} \, (i, j = 1, 2, \cdots, N; i \neq j) \tag{29}$$

where x is any point in the planned area.

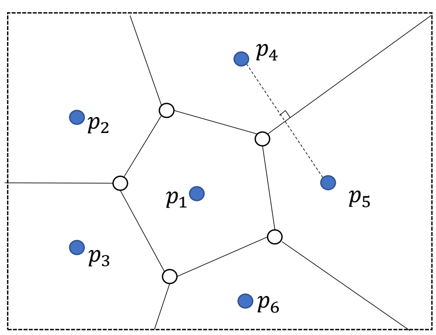


Figure 3: The Voronoi diagram ($N = 6$)

4. Empirical analysis

4.1. Overview of the planning system

The proposed algorithm is applied to the charging station planning for a new developing town - Yizhuang in Beijing in reality. The total area of Yizhuang new town is around 225 km^2 ($39°69'$N-$39°81'$N, $116°53'$E-$116°63'$E). As shown in Fig. (4), the highlighted lines are the main streets in this area, while the red line is for the expressway and the blue line is for the major road. The intersections of those expressways and major roads are indexed from 1 to 27 in this case study. Four major functional zones are circumscribed and distributed in the planning area: one commercial zone, two residential zones, and one industrial zone (PGBM, 2021). In Yizhuang, the two residential zones account for more than 60% of the population.

As one of the major developing zones, Yizhuang has been planned as an innovative global industrial cluster, science and technology service hub. There will be 870 thousand permanent residents and much more traffic would be expected between Yizhuang and the other regions of Beijing after 2035. As shown in Fig. (4), the traffic flow of the intersections at the edge of the planning area (i.e. intersections 1-4, 8, 10-14, 21-23 and 26-27) will be calculated using the equation (2) considering the population mobility between Yizhuang and surrounding areas. Currently, the Yizhuang new town has 11 regions, with approximately 200 thousand vehicles, and EVs share around 8%. According to the 14th five-year plan, there will be 230 thousand vehicles in the new town, with an EV penetration rate reaching roughly 18% (Wong, 2022). To meet the increasing EV charging demand, the availability of public charging infrastructure is an especially important consideration for EV drivers in Beijing due to several limitations. First, many households lack access to dedicated parking spots near home; Even for drivers with such dedicated parking spots, installing home chargers may take several months and need to make an official request to the grid company, district management department and the civil preparedness bureau (CGEP, 2019; ICCT, 2019; Wu and Yang, 2020). Therefore, public charging stations would be the best option to satisfy future charging requirements given the aforementioned limitations of installing home charging infrastructure in Beijing.

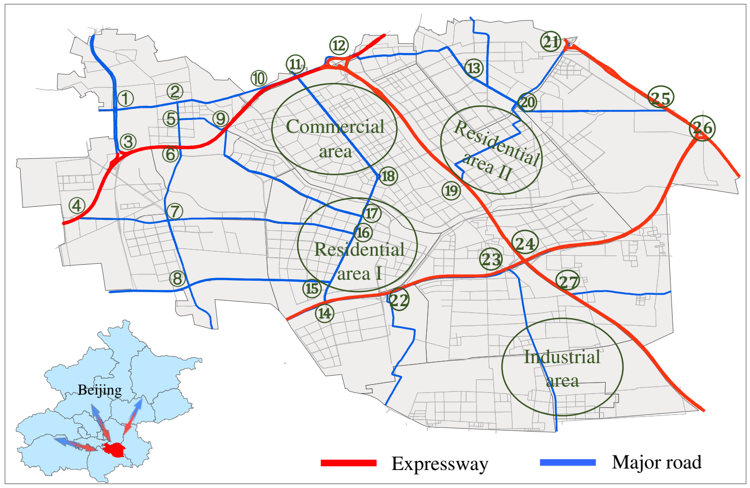


Figure 4: The Yizhuang new town in Beijing

4.2. Data collection and scenario design

In this study, the relevant parameters and unit pricing information of various equipment are from the Beijing traffic development annual report and Beijing statistical yearbook, and technical data is from government official publications, published papers, and surveys (NationalData; BMCDR, 2016). For the gravity model, the population size of main crossings is computed by mobile signaling data, with a radius of $1km$ centered on each intersection. There are nine months of actual data, based on which the left three months (April, May, and October) of data are simulated since the objective is to optimize the annual cost in the experiment.

The service level grading of Beijing roads is shown in table (1). The service level reflects the comfort level of drivers on the road under different traffic conditions. Level 1 means that the driver feels very comfortable and convenient; while with the increase of traffic flow, the service level drops and traffic congestion occurs; Level 4 indicates that the driver is seriously disturbed by other vehicles or pedestrians. In other words, the service level of one road changes with time. For example, during rush hours, the traffic flow is large and the road service level is low; then at this time, the driving speed of vehicles on the road will also be small. The speed of EVs at different time periods in equation (19) is based on the table (1).

Table 1: The service level grading of different roads in Beijing

Grading standard			Service level			
	Free flow velocity	Index	1st	2nd	3rd	4th
Expressway	$70km/h$	Minimum velocity $/km \cdot h^{-1}$	64	57	47	33
		Maximum load degree v/c	0.28	0.57	0.85	1.00
	$80km/h$	Minimum velocity $/km \cdot h^{-1}$	73	65	54	40
		Maximum load degree v/c	0.32	0.59	0.87	1.00
	$90km/h$	Minimum velocity $/km \cdot h^{-1}$	81	73	59	45
		Maximum load degree v/c	0.34	0.6	0.89	1.00
Major road	$50km/h$	Minimum velocity $/km \cdot h^{-1}$	40	35	28	20
		Maximum load degree v/c	0.35	0.65	0.85	1.00
	$60km/h$	Minimum velocity $/km \cdot h^{-1}$	50	44	30	22
		Maximum load degree v/c	0.38	0.68	0.87	1.00
	$70km/h$	Minimum velocity $/km \cdot h^{-1}$	60	52	38	25
		Maximum load degree v/c	0.40	0.70	0.89	1.00

When planning charging stations, various assumptions (such as the maximum number of charging piles in each station, the maximum queuing time for EVs, etc.) must be considered (Shahraki et al., 2015).

1) There are two types of charging piles in each station, 120kw DC fast charging pile and 7.7kw AC slow charging pile;

2) The number of charging piles for compact EVs at each station is limited to 50 due to the space constraint;

3) The life span of each station is set to be 20 years.

4) The queuing time for each EV is no more than 20 minutes;

5) The cost of time is set to be 10 $\$/h$ based on the local average wage.

For the sake of simplicity and generality, we assume that compact EVs are unified as Biyadi yuan, which has a rated battery capacity of $50.1kwh$, a power consumption of 14 kwh per 100 kilometers, and a maximum range of 401 kilometers. For the traffic system, the transportation road network is simplified, and only expressways and major roads are considered. The charging demand distribution and the locations of charging stations are calculated based on the traffic flow at the intersections of these roads. Furthermore, the parameters of the optimal model are identified according to the following table (2), where the charging efficiency is the conversion efficiency of the consumed energy per ampere hour (AH); the cable and assembling contains the cost of labor, cable (16 mm^2) and PVC casing wiring; the material of car shed is mainly aluminum alloy and poly-carbonate plate.

Table 2: The model parameters setting

Parameters	Value	Parameter	Value
charging efficiency	0.95	electricity price (slow charge)	0.13 $\$/kwh$
cable and assembling cost	8.6 $\$/m$	car shed cost	71.8 $\$/m^2$
tortuosity coefficient of power line	1.5	land rental	30 $\$/(m^2 \cdot year)$
line loss rate	8%	charging loss rate	10%
transformer loss rate (400 kw)	1.08%	transformer loss rate (1250 kw)	0.96%
transformer loss rate (2000 kw)	0.73%	electricity price (fast charge)	0.17 $\$/kwh$
parking space area	12 m^2	DC charging pile capacity	120 kw
DC charging pile cost	7033.5 $	AC chariging pile capacity	7.7 kw
AC charging pile cost	215 $	transformer cost (400 kw)	6330 $
transformer cost (1250 kw)	11336 $	transformer cost (2000 kw)	17651 $
maximum queue time q_{max}	20 min	maximum drive distance l_{max}	5 km
maximum capacity of node r $S_{r,max}$	3 MW	minimum distance of stations d_{min}	1 km
maximum power capacity S_{max}	60 MW	lower limit rate α_{lower}	-3%
upper limit rate α_{upper}	+7%	rated voltage U_0	35 KV

5. Results and discussions

In this section, the actual system will be used to assess the effectiveness of the proposed strategy. According to the Yizhuang new town development plan, about 40 thousand EVs are introduced in the system. Based on the traffic flow in equation (2), a certain proportion of EVs is introduced to the traffic system, including 24000 private cars, 10000 taxis, and 6000 other vehicles (Zou et al., 2016). For the percentage of mileage per hour to daily mileage and its probability density curve, parameters in the mixed Gaussian function are estimated as follows: $\pi_1 = 0.078, \mu_1 = 14.86, \sigma_1 = 5.31; \pi_2 = 0.051, \mu_2 =$

$8.75, \sigma_2 = 3.11$. For the SOC of EVs when they get charged and its probability density function, parameters in the Weibull distribution are estimated as $a = 6.31$ and $b = 1.67$.

5.1. Charging demand distribution

Fig. (5) shows the number of different types of EVs at each traffic intersection in a day. It is evident that the distribution of EVs is uneven, which is related to regional functionality. More than 1000 electric private cars are crossing the traffic intersections 9-20, which are located near residential and business zones with high population mobility. According to the development plan of the Yizhuang new town, there would still be some less developed areas in 2025. Since these regions are sparsely populated, the traffic flow will be less accordingly, such as the intersections 3, 4, 25 and 26. The electrical taxis have no fixed driving routes and thus the numbers of taxis at different intersections vary slightly. Moreover, the number of taxis in remote places also decreases significantly due to the passengers demand. Other types of vehicles are also used in densely populated regions, like private cars and taxis.

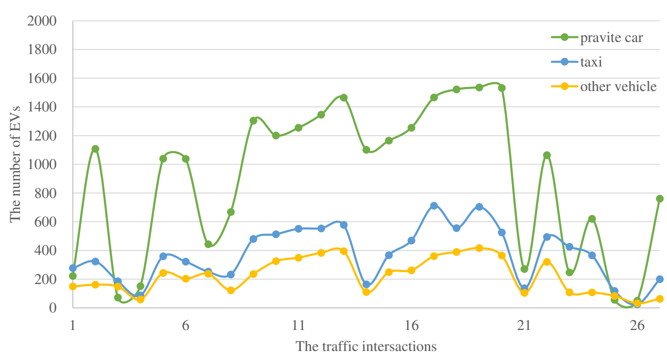
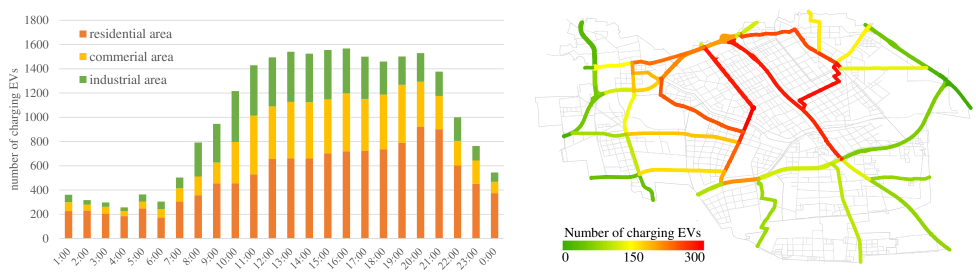


Figure 5: The number of EVs at each intersection

We could obtain the temporal distribution of charging demand in different functional zones, as shown in Fig. 6(a). The peak value of overall charging demand occurs between 13:00 and 18:00. In the two residential zones, the charging demand fluctuates throughout time, from low in the early morning to high between 17:00 and 21:00. This is due to the fact that EVs need to be charged when drivers return home from work. For the commercial zone, there is a large demand for charging from 10:00 to 20:00 in order to meet people's shopping activities. Similarly, there is also little demand for night charging in the business district. The charging demand in the industrial zone is extremely high during working hours from 8:00 to 17:00, which indicates that most people will charge their EVs during working hours before driving back home.

As illustrated in Fig. 6(b), the geographical distribution of charging demand is not even. Residential charging demand is higher than commercial charging demand, whereas industrial charging demand is the lowest. The peak intensive charging demand areas are primarily located around residential and commercial zones, which indicates that the requirement for charging is correlated to the population density. There are mainly factories in the industrial district which is sparsely populated, resulting in a low charging demand. While the population density of residential and commercial zones is relatively large, hence the charging demand is also high accordingly. This information could serve as the basis for planning the charging stations.



(a) The temporal distribution of charging demand (b) The spatial distribution of charging demand

Figure 6: The temporal and spatial distribution of charging demand

5.2. Optimal configuration of charging stations

Based on the temporal and spatial features of charging demand, the overall arrangement of charging facilities in the planning area could be optimized. The comparison of different optimal schemes is shown in table (3). The detailed deployment of different numbers of charging stations is shown in table (5) in Appendix. When the number of charging facilities increases, the cost of drivers (sum cost of driving time and power, queuing time at charging stations) decreases accordingly, while the investment cost from the supply side (including the construction, operation, maintenance and loss cost) increases. The total cost decreases first and then increases with the number of charging stations, which can be explained as follows. When there are fewer charging facilities, less construction and operation related cost is needed, leading to lower annual investment cost. However, the fewer charging facilities can not meet the charging demand in the planning area, which implies a long driving distance when drivers go to charge and a relatively long queuing time at charging stations, thus resulting in a high cost for EVs. When there are more charging facilities located in the planning area, the driving distance and queuing time decrease, which implies that the planning offers more convenience for drivers, thereby offsetting the increased investment cost. At this stage, the total cost also decreases since the ratio of drivers' cost to overall cost is much higher. If the number of charging stations reaches a certain value, the proportion of investment cost would be bigger than the cost of EVs. Thus, the overall system cost would increase with the continuous increase of the number of charging stations. When there are more than 13 charging stations, the small cost of driving and queuing time indicates that there are abundant charging facilities for EVs and drivers do not need to spend too much for charging. While on the other hand, the investment cost is much higher which indicates a waste of resources. In summary, according to the trend of the overall cost for the whole system, the optimal number of public charging stations is determined to be 12.

The optimal planning of charging facilities covers location and scale for each station, as illustrated in table (4). From the latitude and longitude of the planned stations, it is evident that these charging stations are widely scattered across the planning area. The capacity of these charging stations varies hugely. For instance, the 3rd station has the smallest capacity, with only 10 slow charging piles and 5 fast charging piles, followed by the 4th and 10th stations. The

Table 3: Comparison of optimal schemes ($\times 10^3$\$)

The number of charging stations	travel cost	travel and queue time	construction cost	operation and maintenance cost	loss cost	total cost
9	78.37	256.63	228.26	46.92	74.94	685.12
10	60.50	240.06	238.81	48.91	81.57	669.85
11	56.06	191.43	268.87	57.22	88.32	661.89
12	36.57	182.51	287.86	60.14	92.55	659.63
13	37.03	177.83	306.80	70.48	98.38	690.53
14	36.61	170.09	325.58	75.09	101.32	708.70
15	35.55	160.54	333.82	78.61	105.48	714.00

Table 4: Configuration of optimal planning scheme

No.	Longitude	Latitude	Quantity of slow charging piles	Quantity of fast charging piles
1	116.673	39.694	19	10
2	116.489	39.795	26	14
3	116.441	39.746	10	5
4	116.443	39.783	12	7
5	116.541	39.772	17	11
6	116.572	39.798	23	13
7	116.511	39.811	35	15
8	116.494	39.813	31	15
9	116.501	39.757	25	12
10	116.509	39.733	11	7
11	116.539	39.810	29	14
12	116.574	39.719	21	10

7th station has the biggest capacity, with 35 slow charging piles and 15 fast charging piles. It should be noted that the layout of these charging stations is the optimal result of the planning model developed in this article, and it is based on the local traffic flows and charging demand information. During the implementation phase, factors such as the local construction requirements and historical conditions should also be taken into account.

Fig. 7 (a) illustrates the optimal planning layout of the charging stations. It reveals that nine charging stations are distributed around areas with a high population and high traffic flow, whereas only three stations are scattered in the regions with a relatively small population and few roadways. The 1st, 2nd and 8th charging stations are located in the commercial zone, and there are 70 slow charging piles and 39 fast charging piles in total, which could satisfy the charging demand in this region. The next highly concentrated regions are the two residential areas with the provision of the 5th. 6th, 10th and 12th charging stations. Each of these four charging stations has around 30 charging piles except for the 10th station. The 10th charging station is located at the edge of residential area I, indicating a lower level of charging demand than the other three charging stations. There is one charging station numbered 9 near the industrial zone, with more than 35 piles in total. Only a few charging facilities are constructed in the other less populated areas, such as the 3rd and 4th charging stations. There are less than 20 charging piles in these two charging stations, which is related to the small population and traffic flow in these areas.

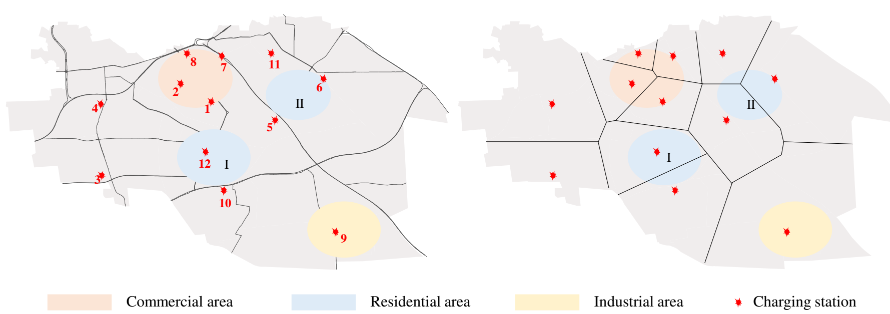


Figure 7: The configuration and service area of charging stations

5.3. Service boundary of charging stations

Since the twelve charging stations have been placed in the planning area, their appropriate service boundary $R_k (k = 1, 2, \cdots, 12)$ could be automatically divided by the Voronoi diagram. Based on the configuration, the optimized service range of each charging station could be obtained, as shown in Fig. 7 (b). The red points denote the charging stations and the black lines represent the service boundaries for each charging station. The service areas of the 4th, 6th, and 9th stations are the top three, consistent with the small populations and low charging demand in these districts. The 7th and 8th stations have minor service areas in the planning area, which is in line with the high population density in the commercial districts. The residential neighborhoods are assigned five stations, and the industrial zone is primarily served by charging station number 9.

According to the experimental results, the implementation of charging stations in the Yizhuang new town could fulfil the charging demand and provide good service for EV drivers. At the same time, the optimized planning prevents the waste of social resources due to disorganized charging infrastructure.

6. Impact of EVs' charging demand

In order to analyze the power load of each functional area, Fig. (8) shows the power demand distribution of EVs and a basic load of these areas. For residential zone I and II, the power demand appears as a 'dual peak' pattern since the charging load and the basic load are both primarily concentrated at around 20:00 in the evening, which is consistent with the residents' mobility patterns. For residential zone I, the charging peak value is about 31.04% of the peak basic load and the ratio reaches 35.31% in residential zone II. As for the commercial zone, the charging load is overlaid on the original basic demand. Due to the long business time, the charging peak period stretches a wide range, from 10:00 to 20:00. The charging load value is about 50.2% of the basic load at around 16:00. The charging demand of the industrial area is mainly spread during working hours with the peak is about 45% of the basic load occurring at 13:00. In conclusion, the charging demands of different functional areas have different distribution features; the peak values of charging demand may bring significant challenges to the power grid operation, and the results presented here could be used to guide the grid operation in these districts. Furthermore, the characteristics of charging requirements in these regions are in alignment with real-world conditions, demonstrating the effectiveness of the proposed algorithm.

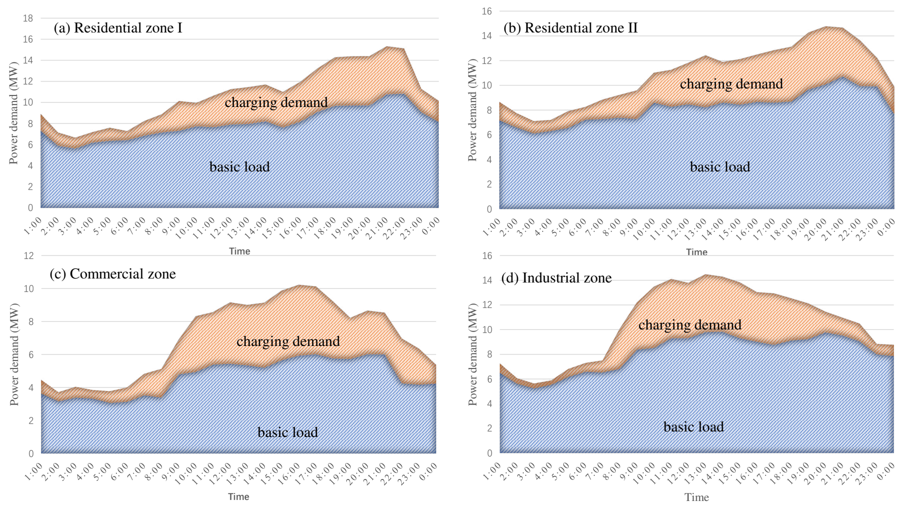


Figure 8: The power demand for different areas

To meet the needs of large-scale development of EVs in the next decades, Fig. (9) shows the charging power demand under different market penetration rates of EVs in the whole planning area. As shown in fig. (9), taking the basic load as a baseline, the charging demand continues to rise along with the penetration rate of EVs. When the market share of EVs is 18%, the charging demand of EVs is less than the basic load for a whole day (24 hours). While the charging demand is greater than the basic load at peak hours (18:00-20:00) when the EVs' penetration reaches 25%. The charging requirement will be 28.6% greater than the basic load during the peak period when the penetration rate of EVs reaches 40%. When this penetration rate reaches 50%, the peak value of charging demand is 47.6% bigger than the basic load, which may jeopardize the power grid's operation safety. In conclusion, with the continuous growth of EV numbers, the increase of EV charging load will account for a higher proportion in the power grid system. Therefore, the EV charging demand and charging infrastructure should be properly analyzed and predicted, as this information will be extremely important for power network planning and operation.

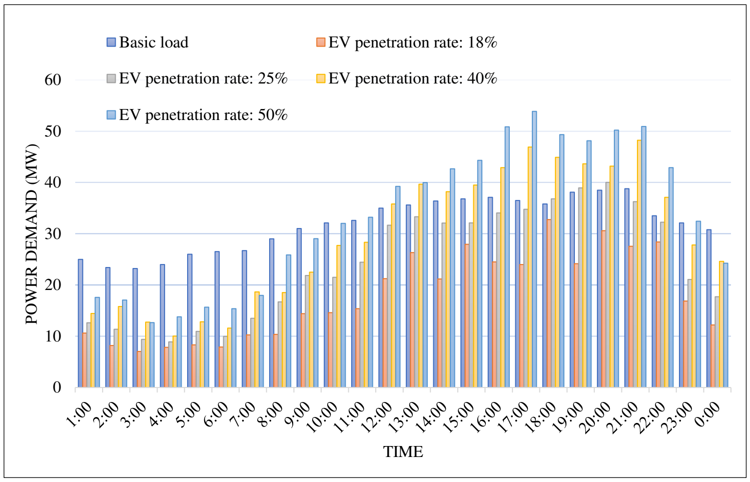


Figure 9: The charging load under different EVs' penetration rates

7. Conclusion

This study has proposed an optimization method for planning the charging facilities considering the dynamic traffic system in a new developing metropolis area. Different from existing optimization approaches, the proposed model considers the spatio-temporal patterns of EV charging demand, providing a more comprehensive framework to examine relevant factors and ensuring the optimization results fit reality.

The proposed model has been used for the charging station planning of the Yizhuang new town in Beijing. Several conclusions that could be drawn from this study: 1) the spatio-temporal features of the traffic flow and charging demand could provide a useful baseline for charging facility planning. 2) The number of EVs at each traffic intersection varies, which is consistent with the population density and regional functionalities. 3) The planning of the optimized charging stations in Yizhuang new town is provided, and the service areas of these stations are determined using the Voronoi diagram. 4) The charging load would be 47.6% greater than the basic load during peak time when the EV penetration rate reaches 50%, which may pose a risk to the power grid operation safety.

It should be noted however that several assumptions are made in the model formulation, which may lead to some limitations and could be addressed in future research: 1) The driving speeds of EVs at different time periods are estimated based on the minimum velocities under different road service levels. 2) The road network is simplified in the study, only including expressways and major roads. 3) The charging demand distribution is calculated from the traffic flow at intersections. 4) In the practical implementation, the location of charging stations should consider a few practical issues such as the site's construction conditions and the historical conditions. 5) EVs could be used as energy storage in the distributed energy system, which would bring additional benefits to different stakeholders.

8. Appendix

Table 5: Results of optimal planning scheme

No.	Longitude	Latitude	Quantity of slow charging piles	Quantity of fast charging piles
1	116.505	39.782	30	14
2	116.468	39.786	28	10
3	116.465	39.751	25	11
4	116.521	39.811	27	15
5	116.557	39.731	25	11
6	116.549	39.776	21	13
7	116.603	39.766	19	9
8	116.496	39.813	22	10
9	116.523	39.757	18	9
1	116.501	39.782	31	16
2	116.503	39.81	28	15

3	116.508	39.753	28	16
4	116.451	39.784	20	11
5	116.554	39.734	23	12
6	116.558	39.787	19	10
7	116.541	39.812	20	11
8	116.494	39.731	19	8
9	116.474	39.803	15	6
10	116.591	39.766	17	8
1	116.481	39.805	26	13
2	116.485	39.779	22	10
3	116.441	39.794	17	9
4	116.428	39.769	16	9
5	116.482	39.753	19	10
6	116.524	39.748	20	12
7	116.573	39.715	20	11
8	116.554	39.782	24	11
9	116.544	39.807	18	10
10	116.591	39.798	21	9
11	116.513	39.801	28	15
1	116.488	39.792	18	8
2	116.497	39.809	22	10
3	116.516	39.783	17	9
4	116.497	39.764	21	13
5	116.507	39.748	25	12
6	116.455	39.752	14	8
7	116.441	39.786	19	8
8	116.527	39.748	12	7
9	116.562	39.726	18	11
10	116.535	39.804	24	12
11	116.567	39.782	30	16

12	116.555	39.801	28	12
13	116.606	39.767	8	4
1	116.484	39.797	18	11
2	116.495	39.781	24	10
3	116.503	39.809	14	8
4	116.529	39.796	26	12
5	116.538	39.814	9	4
6	116.553	37.783	17	9
7	116.513	39.761	20	10
8	116.492	39.749	19	9
9	116.451	39.752	14	6
10	116.452	39.783	27	12
11	116.591	39.794	30	14
12	116.569	39.758	10	5
13	116.562	39.721	20	13
14	116.519	39.779	18	11
1	116.486	39.805	20	11
2	116.481	39.787	15	7
3	116.506	39.799	17	9
4	116.514	39.816	18	10
5	116.571	39.798	21	12
6	116.521	39.776	13	6
7	116.497	39.764	14	8
8	116.504	39.746	17	9
9	116.463	39.756	23	10
10	116.447	39.783	19	7
11	116.553	39.803	28	15
12	116.594	39.768	21	10
13	116.575	39.718	18	6
14	116.511	39.76	13	7

15	116.551	39.78	16	7

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