The measurement method of spatiotemporal accessibility of electric vehicle charging stations in the dynamic time-dependent urban environment

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Abstract. The accessibility of electric vehicle charging stations (EVCS) is one of the critical factors affecting energy vehicles' development. It is also the root cause restricting the replacement of fuel vehicles by new energy vehicles. All kinds of dynamic factors in the city, such as population and traffic, will directly affect the spatiotemporal accessibility of charging service facilities. Therefore, exploring the measurement method of EVCS spatiotemporal accessibility in dynamic time-dependent environments can reduce idleness, alleviate queuing pressure, and promote new energy vehicles. Taking Nanjing as an example, this paper conducts research based on multiply time slots, mobile phone records, and online route planners. It uses population data dynamic effect measurement methods, traffic congestion coefficients, and 3SFCA based spatiotemporal accessibility models to evaluate the time slot changes of EVCS accessibility. The results show that with the changes of the urban population, occupation, residence, work, and leisure, the accessibility of EVCS presents prominent "polarization" characteristics and dynamic effects. It is recommended to formulate new and adjust the deployment plan of EVCS according to the dynamic changes of the urban population, traffic environment, and accessibility in multiply time slots to reduce idleness and queuing and improve the utilization rate of EVCS.

1. Introduction

Greenhouse gas emissions are one of the main factors of global warming. According to statistics, greenhouse gas emissions caused by the European Union transportation sector account for 74% of total energy consumption [1], accounting for a relatively large proportion. New energy electric vehicles are regarded as a means of transportation that may reduce greenhouse gas emissions [2]. Their promotion has become an essential means of energy-saving and emission reduction. To promote the rise of new energy electric vehicles, must adopt a variety of standards to determine the location of suitable charging stations and improve the utilization rate of charging stations. Compared with the policy planning, the construction of EVCS is lagging. It presents the dilemma of unbalanced spatial layout, long-term queuing of charging in dense demand areas, and utterly idle charging piles in some low demand areas, which dramatically affects the user's charging experience. How to reasonably evaluate the spatial layout of EVCS and optimize the spatial configuration of EVCS is of great significance for improving the utilization efficiency of EVCS and improving the charging convenience of travelers.

EVCS utilization efficiency factors mainly include the spatial allocation of charging infrastructure, user driving behavior, and external environment. Among them, the spatial allocation of charging infrastructure is the most direct factor affecting the utilization efficiency. Scholars in geography and urban planning have studied the spatial allocation of charging infrastructure from two aspects: (1)
evaluation of the current spatial distribution of EVCS, (2) spatial optimization of EVCS. Among them, the evaluation of the current spatial distribution of EVCS mainly includes accessibility evaluation, queuing time evaluation, fairness evaluation, and so on. Spatial optimization has EVCS site selection [3], charging, and matching capacity of EVCS [4]. Among them, accessibility is a critical way to measure efficiency, and the commonly used methods to measure accessibility include network analysis, distance method, cumulative opportunity method, and so on. Tao, Cheng and Liu [5] used the hierarchical two-step floating catching area (2SFCA) method to measure the spatial accessibility of layered facilities. Akbari [6], considering the queuing time and charging efficiency, adopted the Poisson process to represent the charging events of each station and analyzed its accessibility. The existing research data of EVCS evaluation are mainly static panel statistics data [7], this kind of data lacks the records of dynamic population distribution and traffic congestion conditions at different time slots, so it can't reflect the time slot characteristics of charging demand changes in other locations of cities caused by time slot changes. Previous studies have proved that the actual demand and utilization rate of EVCS will fluctuate with the change of dynamic urban environment, such as the change of EVCS charging demand time slot caused by commuting between work and residence.

Under the traditional static mode, the spatial allocation of service facilities based on index transmission and layout is challenging to adapt to the high utilization efficiency of service facilities' spatial allocation in megacities. The contradiction between charging difficulty and a large amount of idle has become increasingly prominent, and static data can no longer truly reflect reality. The development of big geographic data provides a new way to study EVCS. Hidalgo [8] used big Internet data to study travelers' daily activities and spatial distribution and analyze the demand of EVCS. Han [9] used the existing travel data tracked by EV to conduct modeling analysis and evaluate the possession of EVCS. Yagcitekin [10] built the EVCS positioning model based on the Agent method. It can be seen that the research on EVCS with dynamic time slot changes can map the real scene more accurately, and the research on EVCS accessibility in a dynamic time-dependent urban environment has essential research value.

Therefore, this paper will use multiply time slots traffic route planning data, multiply time slots activity population spatial distribution data, and EVCS spatial distribution data to measure the dynamic effect of urban active population and traffic environment by using population variation coefficient and traffic congestion coefficient, based on three-step floating catchment area method (3SFCA) accessibility evaluation method of the dynamic effects to analyze the accessibility time slot variation characteristics of city dynamic environment EVCS, and provide a reference for planning decision.

2. Research area and data

2.1. location introduction

Nanjing, the capital of Jiangsu Province, is one of the four ancient capitals and famous cultural cities in China. It has the reputation of "the world's literary pivot". Nanjing is located at 31 14 ~ 32 37" north latitude and 118 22 ~ 119 14" east longitude, with a total area of 6587 square kilometers. It belongs to the subtropical monsoon climate. The landform features belong to Ningzhenyang hilly area, with low mountains and slow hills as the main features. Nanjing is China's regional central city and megacity, and the Yangtze River Delta radiation drives the midwest areas' development. In 2020, Nanjing's GDP was 1,481.795 billion Yuan, ranking 10th in China, and its comprehensive strength ranks 5th in China.

As of 2020, Nanjing has jurisdiction over 11 municipal districts, including Gulou, Qinhuai, Qixia, Jianye, Yuhuatai, Xuanwu, Jiangning, Pukou, Gaochun, Lishui, and Liuhe. Nanjing has a resident population of 8.5 million. Nanjing has opened two tram lines, six river crossings channels, and nine rail transit lines, with 8,395 buses and trolleybuses, 14,628 taxis, and ten subway lines. Besides, as of the end of 2018, the number of private cars in Nanjing reached 2.54 million, and the number of shared bicycles and electric bicycles reached 650,000 and 3 million, respectively. In summary, considering the typicality of Nanjing's population size and economic location, Nanjing, a megacity, is selected as the study area of this paper (Figure 1). To facilitate the classification and discussion of the study area, the
concepts of central urban areas, neighboring suburbs, peripheral suburbs are illustrated for the study area. Among them, the central urban areas are defined as six urban districts, including Gulou, Qinhuai, Qixia, Jianye, Yuhuatai, and Xuanwu District; the neighboring suburbs are areas close to the central urban areas, including Jiangning and Pukou District; the peripheral suburbs are peripheral towns far away from the central urban areas, including Gaochun, Lishui and Liuhe District.

![Figure 1. Study area](image)

### 2.2. Description of research data

This paper's research data include: multiply time slots traffic route planning data based on web mapping platforms, multiply time slots activity population spatial distribution data based on mobile phone records, and EVCS spatial distribution data. In order to facilitate visualization and data analysis, this paper selects four representative time periods: 8:00 (morning commuter peak), 13:00 (daytime commuter trough), 18:00 (evening commuter peak), and 22:00 (nighttime commuter trough) [11, 12] for accessibility analysis, these four time periods can effectively reflect the periodic dynamic time-dependent urban environmental changes caused by economic activities and commuting between work and residence.

### 2.3. Multiply time slots traffic path planning data

In the research of reachability measurement, clarifying the correct traffic time or spatial distance plays a vital role in describing the spatial damping and spatial interaction between the service party and the demander. Therefore, a way is needed to obtain accurate traffic time or spatial distance data as much as possible. There are concentric circle method, Thiessen polygon method, and path planning method to get traffic time or spatial distance. The path planning method is the most suitable for the characteristics of actual residents' travel behavior. This paper uses the request for web mapping route planning API to obtain the time distance data of multiply time slots traffic planning and selects Amap (www.amap.com) as the data source. It can combine real-time traffic data with destinations, departure points, and road policies to help travelers bypass congested roads, provide real-time navigation, and customize travel plans [13]. The route planning API of the Amap is very convenient to retrieve. It just sends the latitude/longitude coordinates of the demand location and the provider location into the API as parameters. Then, the API interface returns the results. The particular operator structure is as follows (Table 1).

| Table 1. Operator pseudo-code of path planning API request to obtain time interval |
|---------------------------------------------------------------|
| **Operator:** Based on the route planning API of web mapping platforms to obtain the travel distance and time operator of traffic OD flow |
Importing: demand location coordinates \((px_i, py_i)\), provider location coordinates \((px_j, py_j)\), traffic type, the distance threshold

Output: the distance and time between the starting point and the demand location according to the given traffic type at the current request time slot

3. If \(\sqrt{(px_i - px_j)^2 + (py_i - py_j)^2} \gg\) distance threshold then:

4. Return 999,999

5. Request the route planning API of web mapping platforms, return the JSON object and store it in result. The request form is: request.url (http://restapi.Amap.COM/V3/direction/traffic type?Origin=(px_i,py_i)&destination=(px_j,py_j)&Output=JSON&key=<user's key>), and the result is stored in the JSON object

6. Analyze the JSON object to obtain the travel distance and time of the route

7. Return the travel distance and time

Based on the above method, the OD flow traffic time between EVCS and the demand point in the study area at the four-time slots is obtained and filtered according to the time threshold. Considering the large number of EVCS, it is difficult to characterize the high-dimensional OD flow data in general spatial expression form. The OD flow between EVCS and demand point is dynamically rendered by kepler.gl, clearly reflecting the relationship between EVCS and demand points (Figure 2(a)).

2.4. Spatial distribution data of active population at multiply time slots

Mobile phone records are a kind of signaling data serving mobile communication. It is also a new big geo-data source for carrying out urban scientific research and building smart cities [14]. The mobile phone records are generated by the mobile phone user's communication base station of the operator capturing and recording the signaling track of the same user when the mobile phone user calls, sends short messages, or moves the location, and mainly includes encrypted user identification, timestamp, and other contents. It has the advantages of full coverage, high accuracy, real-time dynamics, information relevance, and so on. Census data often assume that the population distribution is uniform and does not change with time, but due to personal travel activities such as life and work, the population has specific mobility, and the census data cannot meet the research needs. The mobile phone records data as the population data with high spatiotemporal resolution can better meet the requirements.

In this paper, the mobile phone records data of Nanjing in the first week of April 2019 is extracted, and the population distribution in this period is relatively stable. According to the data characteristics of the existing active population and the law of population activity, the number of active population at 9:00 and 21:00 was selected to represent the population during the daytime and nighttime. From the overall observation of the study area, the number of recorded users in the daytime is about 1.8 times that at nighttime. The reason is presumed to be the difference in the overall proportion of the active population at different time slots. To solve the difference of data quantity at different time slots, according to the principle that the total population of the whole city is equal at each time slot, taking 8.5 million permanent residents in Nanjing in 2019 as the total data, and the active population in each period is standardized in proportion according to the total number of permanent residents, to obtain the spatial distribution data of permanent resident population at each time slot (Figure 2(b)). It can be seen that the population in Nanjing changes dynamically in the temporal and spatial dimensions, and the main urban area is the most obvious.
2.5. EVCS spatial distribution data

With the promotion of EV, EVCS has become the focus of the automobile industry and energy industry development, effectively solving fast charging limitations. EVCS is a charging station that the public and residents can use to meet the demand for fast charging of various EVs in the city. EVCS mainly includes special charging stations for units, special charging stations for residential quarters, special charging stations for buses and taxis, charging stations for expressway service areas, and urban public charging stations (Figure 3) [15]. The EVCS studied in this paper mainly refers to the public service-oriented urban public charging station, which is different from serving people of specific types and locations.

In this paper, the web mapping platform, Amap, is used as the data acquisition source of EVCS. Amap launched the charging map service in April 2020 to provide the one-stop charging body for vehicle owners, including the location of EVCS, the number of charging piles, price, status, and other real-time information, which has good timeliness and authenticity. Combined with field investigation, based on the charging map of Amap, more than 400 EVCS, including 3925 piles (Figure 1), were requested, analyzed, and obtained in Nanjing. It can be concluded that the spatial distribution of EVCS is the densest in the central urban areas and sparsely distributed in the peripheral suburbs.
3. Methods
The dynamic effect measurement method of population data is used to show the change degree of population, and then use the obtained traffic data to receive the OD flow, measure the traffic congestion coefficient. Then the time slot $t$ is introduced into the original accessibility method to obtain the spatiotemporal accessibility of charging service facilities at the different time slot.

3.1. Measurement method of the dynamic effect of population data
The increasing rate can effectively describe the change of population in the region. Still, it is insufficient to explain the significance of the change of the whole population in the area. Therefore, the coefficient of variation (CV) is introduced to describe the importance of the variation of the population in each time slot. CV is the standard deviation ratio and the average of the data to describe the degree of dispersion [16]. In this paper, the dispersion degree of the population is calculated from two dimensions of time and space, and the calculation formula is as follows:

$$c_{vs} = \frac{\delta_s}{\mu_s}$$  \hspace{1cm} (1)
$$c_{vt} = \frac{\delta_t}{\mu_t}$$  \hspace{1cm} (2)

Where, $c_{vs}$ - the spatial variation coefficient; $c_{vt}$ - the time variation coefficient; $\delta_s$ - the population standard variation of the region $s$ at 24-time slots of the day; $\mu_s$ - the average population at 24-time slots in the whole day; $\delta_t$ - the standard variation of the population of the entire region at time slot $t$; $\mu_t$ - the mean value of the population of the entire region at time slot $t$.

The larger the spatial and time dispersion coefficients, the stronger the population change ratio's significance.

3.2. Traffic congestion coefficient measurement
Researchers apply a value to measure the degree of spatiotemporal change to directly reflect the comprehensive spatiotemporal variation in geographical features [17]. The dynamic index is widely used in land use type change, as it can depict the general characteristics of the spatiotemporal variation in land use type in multiple years [18]. Based on this inspiration, we design $\gamma_{r}(ij)$ (Equation 3), the traffic congestion coefficient of demand location $i$ to supply point $j$, and $\gamma_{r}(i)$ (Equation 4), traffic congestion coefficient of demand location $i$, to estimate the traffic congestion.

$$\gamma_{r}(ij) = \begin{cases} 
1 - \frac{1}{T} \sum_{t=1}^{T} h^r_{te}(ij) h^{t_0}_{te}(ij), & h^r_{te}(ij) > h^{t_0}_{te}(ij) \\
0, & h^r_{te}(ij) \leq h^{t_0}_{te}(ij)
\end{cases}$$ \hspace{1cm} (3)

$$\gamma_{r}(i) = \sum_{j=1}^{M} \gamma_{r}(ij)$$ \hspace{1cm} (4)

Where, $h^{t_0}_{te}(ij)$ - the benchmark of travel duration of transport mode $r$ at time slot $t_0$ from demand location $i$ to supply location $j$, which is selected 22:00 as $t_0$ in this paper; $T$ - a total of time slots; $M$ - the total number of supply points.

3.3. Accessibility evaluation method
Accessibility of service facilities aims at quantifying the interaction strength among the scale of service facilities, demand scale, and transportation cost, and evaluating the spatial allocation of regional service facilities from the perspective of spatiotemporal interaction, and it is a necessary part of urban planning and urban traffic optimization research [19, 20]. According to different types of service facilities, scholars mainly focus on necessary health care facilities [21], rural supporting facilities [22], the impact of cross-district on service facilities [23], health and emergency services facilities [24] have carried out extensive research.
Wang integrated various evaluation methods of facility spatial accessibility into a unified form [25]. Therefore, the advantages of 2SFCA and the gravity model method can be combined at the same time, and the model can be expressed as:

\[ D_j = \frac{E_j}{\sum_{k=1}^{m} Q_k f(d_{kj})} \quad (5) \]

\[ A_i = \sum_{j=1}^{n} D_j f(d_{ij}) \quad (6) \]

Where, \( A_i \) - the score of accessibility of demand location \( i \); \( E_j \) - the scale of the provider \( j \); \( D_j \) - the supply-demand ratio of provider \( j \); \( Q_k \) - the scale of the demand location \( k(i = 1, 2, \ldots, n) \); \( f \) - the generalized distance decay function; \( d_{ij}(d_{kj}) \) - the travel time between \( i(k) \) and \( j(k = 1, 2, \ldots, m) \); \( m \) - The total number of provider points; \( n \) - the total number of demand points.

The distance decay function used in this paper can be written as follows:

\[ f(d_{ij}) = \begin{cases} d_{ij}^{-\delta}, & d_{ij} \leq d_0 \\ 0, & d_{ij} > d_0 \end{cases} \quad (7) \]

Where, \( d_{ij} \) - travel time between demand points \( i \) and \( j \); \( d_0 \) - travel time threshold, namely search radius; \( \delta \) - distance attenuation parameter. The establishment of distance attenuation parameters has a specific impact on the calculation of reachability. The distance attenuation parameter is set to 1 [26].

2SFCA related methods overestimate the potential population demand when multiple facilities can be used in one population location without considering the competitive potential. Combining the competitive potential between facilities, Wan and others improved 2SFCA and proposed the 3SFCA [27]. 3SFCA assumes that the demand point is affected by the built supply point's cost and the transportation cost to the adjacent service point, which includes an initial step. Before the 2SFCA process, it increases the selection weight of the demand point for facilities, measures the competition effect between multiple facilities located within the search radius of the same demand point, and calculates the selection weight \( G_{ij} \) of all population and facilities. \( G_{ij} \) value expressed as:

\[ G_{ij} = \frac{W_{ij}}{\sum_{k=1}^{m} W_{kj}} \quad (8) \]

Where, \( W_{ij} \) - the selection weight value of demand location \( i \) and provider location \( j \); \( W_{kj} \) - the sum of all weight values of provider location \( k \) in demand location \( i \); \( f \) - the generalized distance decay function; \( d_{ij}(d_{kj}) \) - the travel time between \( i(k) \) and \( j(k = 1, 2, \ldots, m) \).

Substituting the value of \( G_{ij} \) into the Two-step mobile search method of Equation 5 and Equation 6 to obtain 3SFCA.

\[ D_j = \frac{E_j}{\sum_{k=1}^{m} Q_k G_{ij} f(d_{kj})} \quad (9) \]

\[ A_i = \sum_{j=1}^{n} D_j G_{ij} f(d_{ij}) \quad (10) \]

3.4. accessibility evaluation method considering the dynamic effect

In equation 9 and equation 10, without considering the change of time slot, the spatiotemporal accessibility at different time slots is obtained by introducing the time slot \( t \) to the 3SFCA model. The formulas equation 11 and equation 12 are given as:

\[ D_{jt} = \frac{E_j}{\sum_{k=1}^{m} Q_k G_{ij} f(d_{kj})} \quad (11) \]

\[ A_{it} = \sum_{j=1}^{n} D_{jt} G_{ij} f(d_{ij}) \quad (12) \]
\[ D_j^t = \frac{E_j^t}{\sum_{k=1}^{m} Q_k^t c_{ij}^t f(d_{kj})} \]  

\[ A_i^h = \sum_{j=1}^{n} D_j^t G_{ij}^t f(d_{ij}) \]

Where, \( t \) - different time slots, \( t \in (0, T] \). Among them, the connotation of other variables is consistent with the above symbolic meaning.

4. Result

4.1. Dynamic effects of population

The dynamic change of population is mainly produced by residents’ activities, such as commuting, entertainment, leisure, etc. It can be seen that the population of each demand has a significant dynamic effect (Figure 4 (a)), and the degree of change is heterogeneous. The first level area of the dynamic effect of population, that is, the blocks with \( cv_x = 0 \) are mainly distributed in the west of Gaochun District. This area has the smallest permanent population, small population mobility, and small dynamic changes; The second level area of the dynamic effect of population are mainly distributed in the north-central part of the study area, such as the central urban areas, the neighboring suburbs and the Liuhe District in the peripheral suburbs, whose dynamic effect should be more significant. These areas have rapid economic development and a large number of permanent residents, mature urban functional zoning, high-quality service resources and a large number of job opportunities are the main driving factors of population mobility; The third level and fourth level area of the dynamic effect of population are continuously distributed in each urban area. The reason is that the phenomenon of work and residence in these areas is relatively prominent, and the distance between workplace and residence is relatively long, the number of commuting population is large; The fifth level area of the dynamic effect of population is scattered in various urban areas, and the population change are the most significant, such as Liuhe, Jiangning and Lishui in the figure. Because the population density of Nanjing shows a characteristic of decreasing from the central urban areas to the periphery, and the employee has the phenomenon of centripetal commuting, the population mobility in these areas is considerable, and the population change is significant.

The whole region's dynamic population effect is noticeable, and the degree of population change at each time slot presents inevitable volatility. As shown in Figure 4 (b), it can be seen that the dynamic effect of the population in the whole region at night is more substantial than that in the daytime. From 8:00 pm to 4:00 am, the time dispersion coefficient is at a higher value, both greater than 1.7. The two peaks in the daytime appear at the morning commuter peak and evening commuter peak, respectively. At this time, due to the commuting of residents, the population mobility is considerable. After the morning peak and before the evening peak, most residents work hours, so the population mobility is small, so the time dispersion coefficient fluctuates. Only a sub-peak appears at noon.
4.2. Dynamic effect of traffic

On the whole, except for the northern region, the traffic congestion degree of the study area presents a "U-sharp" distribution, which shows a downward trend from the central urban areas to the edge area. The traffic congestion in Gulou, Jianye, Qinhuai, Xuanwu in the central urban areas and Pukou area in the neighboring suburbs is high (Figure 4(c)). The main reason is that Nanjing's employment presents centripetal commuting and the population gathering and strong mobility in this area. The traffic congestion in most Jiangning and Pukou in the neighboring suburbs and Liuhe in the peripheral suburbs is relatively high. The reason is that the adjacent suburbs are close to the main urban areas, the economic development is good, and the population commuting is relatively large, so the traffic congestion problem is more prominent. The population distribution in the peripheral suburbs and the neighboring suburbs of the outskirts is sparse, the mobility is small, and the traffic congestion is little.

4.3. Dynamic accessibility evaluation

The polarization phenomenon of spatial accessibility in Nanjing is evident, which mainly shows that the spatial accessibility value of public charging piles in the peripheral suburbs is high, the spatial accessibility values of central urban areas and neighboring suburbs are low, and the dynamic effect of regional accessibility is significant (Figure 5).

In terms of spatial dimension, the accessibility value of each region in the central urban areas is relatively low, especially Qixia District, where most of the accessibility values are at the first level, while the accessibility values of Gulou, Qinhuai, Jianye, Yuhuatai and Xuanwu District are basically at the second level, which is mainly due to the dense population distribution in the central urban areas and the apparent shortage of EVCS supply. The spatial accessibility value of the neighboring suburbs is low, especially at the edge of Pukou and Jiangning. The main reason is that the population mobility in these areas is relatively prominent. Still, the distribution of public charging piles in this area is relatively sparse, challenging to meet the demand. The spatial accessibility of the peripheral suburbs is relatively high, especially in Liuhe, the southeast of Lishui and Gaochun District, mostly at the fourth and fifth levels, mainly because the area's population is small and its EVCS resources are sufficient to meet the demand.
In the time dimension, due to the flow of population, the accessibility values of each region showed significant changes at four-time slots, among which the peripheral suburbs showed the most apparent performance. The accessibility values of the central urban areas and peripheral suburbs are relatively high at nighttime due to the decrease of night population compared with daytime, and the overall change range is not extensive. The accessibility value of the peripheral suburbs changed significantly, due to the large population mobility in the daytime, the accessibility value of Liuhe was lower than the other two time slots in the morning commuter peak and the evening commuter peak, and the accessibility value is the highest at nighttime; The accessibility value of Lishui decreased in the evening commuter peak but increased sharply at nighttime, and the southern area showed the most prominent performance; the accessibility value of Gaochun showed fluctuating changes at all time slots, compared with the morning commuter peak, the accessibility value increased at noon, decreased to the minimum value in the evening commuter peak, and increased to the maximum value at nighttime.

Figure 5. Spatial distribution of multiply time slots accessibility of built EVCS

Figure 6 shows the histogram distribution, proportional distribution and cumulative distribution characteristics of EVCS accessibility values at four representative time slots. It is not difficult to find that the histogram and pie chart (interval: 0.00-0.05, 0.05-0.10, 0.10-0.15, 0.15-0.20) of the four graphs in Figure 8 show expansion and contraction changes with time slot. Among them, the accessibility
values of morning commuter peak and evening commuter peak are concentrated in 0-0.5, accounting for 87.7% and 88.6% respectively; However, the percentage of accessibility values between 0.00-0.05 during the day and at night decreased to 82.4% and 70.3% respectively. This phenomenon shows that due to the increase of the total number of the active population and the rise of traffic congestion in the morning and evening peak hours, the travel time is increased and the overall accessibility value is concentrated in the low-value areas. Due to the high population mobility at 8:00 in the morning commuter peak and evening commuter peak, the EVCS resource supply is insufficient, and its accessibility is reduced, so the proportion of EVCS in the pie chart is more significant than the other two times slots. Also, through the observation of cumulative curve slope, it is found that the slope of the cumulative curve at the normal commuting time at night is gentle, which indicates that the variation of overall accessibility value distribution at this time slot is lower than at other times slots. It is concluded that the global accessibility of EVCS at different time slots has a significant dynamic effect.

Figure 6. Cumulative distribution diagram

5. Conclusion and discussion
This paper, based on the multiply time slots traffic route planning data, multiply time slots activity population spatial distribution data and EVCS spatial distribution data, carry out research on the spatiotemporal accessibility of charging service facilities under a dynamic time-dependent urban environment and draw the following conclusions: (1) Through the population dynamic effect measurement method, it is found that the population of each block changes to different degrees in a day, which has a significant dynamic effect, the change of population are most influential in the neighboring suburbs and peripheral suburbs. (2) Due to the influence of population aggregation and employment tendency, the traffic congestion degree of Nanjing presents an apparent "circle type" distribution. The central urban areas are more crowded, the neighboring suburbs area is the second, and the peripheral suburbs is smaller. (3) In this paper, the improved 3SFCA method is used to evaluate the spatiotemporal accessibility of charging service facilities in a dynamic time-dependent urban environment. The results show that EVCS accessibility "polarization" characteristics and dynamic effect are apparent. In the spatial dimension, the population distribution in the central urban areas is relatively dense. The EVCS has a noticeable shortage of supply, and its accessibility is low. In the neighboring suburbs, because of the sparse distribution of public charging piles, its accessibility is insufficient; in the peripheral suburbs, because of the sparse population, its accessibility is higher. In the time dimension, due to the population flow, the accessibility values of different regions show significant changes at four-time slots, among which the peripheral suburbs showed the most apparent performance. The accessibility values of the central urban areas and peripheral suburbs are relatively high at nighttime, and the overall change range
is not extensive. This paper's research method can reflect the time slot characteristics of the charging demand change in different city locations caused by time slots’ change. This paper's deficiency is that the mobile phone records data used to obtain the spatial distribution data of activity population at multiply time slots mainly comes from mobile operators. In the future, it is necessary to actively communicate with China Unicom and Telecom operators to obtain the comprehensive location information and stay time of mobile phone users in the whole city. Besides, more forms of distance attenuation function can be introduced when considering the distance attenuation function [28]to enrich the accessibility evaluation of EVCS.

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