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An Electric Taxi Charging Station Planning Scheme Based on an Improved Destination Choice Method

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Abstract: The environmental crisis has prompted the development of electric vehicles as a green and environmentally friendly mode of travel. Since a reasonable layout of electric vehicle (EV) charging stations is the prerequisite for developing the EV industry, obtaining an optimal and efficient EV charging station planning scheme is a key issue. Although the Chinese government has carried out a plan to build EV charging piles in residential and working places, it cannot properly fulfill the task of matching the charging needs for public transportation vehicles such as electric taxis (ETs). How to evaluate the performance of fast charging stations (FCSs) and how to help find the optimal ET charging station planning scheme are new challenges. In this paper, an improved destination selection model is proposed to simulate the ET operation system and to help find the optimal ET charging station size with statistical analysis based on the charging need prediction. A numerical case study shows that the proposed method can address ET charging behavior well and can help to statistically determine the size of each ET charging station, which should satisfy the constraints on the preset proportion of the ET charging service requests.

Keywords: electric taxis; destination selection model; statistical analysis; charging station deployment plan

1. Introduction

Currently, the environmental crisis caused by the explosive growth of the population and economics has attracted much attention.

Electric vehicles (EVs), as a new type of clean transportation choice, can efficiently relieve the crisis by addressing fossil fuel energy shortages, air pollution, and transportation [1]. However, the rapid development of the EV industry presents some new challenges to the current power system [2–5].

In recent years, many researchers have investigated the EV charging station planning problems, especially with the stations' siting and sizing problems.

Because the settings of the EV charging station will have an impact on the local distribution network, researchers have tried to solve the EV charging station location problem. Schroeder et al.

[6] analyze the economics of fast charging infrastructure for EVs in Germany. Lam et al. [7] formulate the EV charging station placement problem and show that the problem is a nondeterministic polynomial-time (NP) hard problem. In reference [8], Ribberink et al. prove the existence of a strong synergy between microcogeneration (micro-CHP) power generation and overnight EV charging. Zhang et al. [9] propose an improved whale optimization algorithm (IWOA) and apply IWOA to solve the locating problem of EV charging stations with service risk constraints. Wan et al. [10] propose a new algorithm for planning charging base stations based on the greedy algorithm and the location relationship of the sensor nodes.

Based on the location problem of EV charging stations, an increasing number of scholars are conducting in-depth research on the capacity of EV charging stations. Liu et al. [11] use a two-step screening method to optimize the sites of EV charging. Reference [12] uses the data-envelopment analysis method to select candidate sites of EV charging stations and then solves the siting problem by the cross-entropy method. Xi et al. [13] optimize the locations of slow chargers to serve EVs. Shukla et al. [14] propose a multiobjective synergistic planning model of an EV charging station considering the power losses and voltage deviation of the distribution system and EV flow served by the fast charging station (FCS). Battapothula et al. [15] present a multiobjective optimization problem to obtain the simultaneous placement and sizing of FCSs and distributed generations (DGs) with constraints such as the number of EVs in all zones and the possible number of FCSs based on the road and electrical network in the proposed system. Benedetto et al. [16] propose a mixed-integer linear procedure for determining the optimal operation planning of a DC-based electric vehicle supply infrastructure. In reference [17], the authors concluded that PV based local DC nano- and microgrids are an excellent option for future energy infrastructure. Liu et al. [18] consider two kinds of charging stations (fast charging stations and normal charging stations) and propose a multiobjective model with the objectives of maximizing the captured traffic flow in traffic networks and minimizing the power loss in distribution networks. Afshin et al. [19] model the fast charging station (FCS) planning problem using a mixed-integer nonlinear programming (MINLP) algorithm, and the Nash bargaining theory is used to analyze the interaction between the distribution company (DISCO) and FCS owner (FCSO). Yang et al. [20] address the sizing (number of chargers and waiting spaces) problem of fast charging stations and present an optimal planning solution based on an explicit temporal-state of charge characterization of PEV fast charging demand.

In addition to studying the impact of charging stations on the distribution network, researchers also incorporate the impact of the EV charging station on EV driving in the research area. In references [21,22], Trip OD matrix information of household travel and dynamic vehicle models are employed to calculate the EV's travel cost, and a linear optimization algorithm is employed to obtain the optimal location scheme of the EV charging stations. In reference [23], historical trajectories are used to simulate the behaviors of EVs. In reference [24], the authors propose the time–space distribution prediction method based on Markov decision process (MDP) random path simulation to solve the randomness of time–space transfer of electric vehicles. Liu et al. [25] propose a comprehensive location selection model for electric vehicle charging stations aiming to minimize the construction cost, operating cost, and convenient transportation of charging stations. Vazifeha et al. [26] propose a modeling–optimization framework to find an efficient layout of charging stations to minimize overall energy overhead and EV drivers' excess driving distance to charging stations. In reference [27], the authors aim to study a novel location planning method for fast charging stations in order to achieve the overall optimization of operators, drivers, vehicles, traffic conditions, and power grids.

Some scholars also pay attention to the impact of battery wear and other control strategies. Liu et al. [28], taking the EV battery capacity constraints of distribution transformers into account, develop a model minimizing the charge–discharge fee of orderly electricity users. Amir A. et al. [29], have examined the issue of electrochemical battery manufacturing of Li-ion and solid-state type from cell-level to battery-level process variability, and proposed potential areas where improvements in the manufacturing process can be made. In reference [30], the authors outlined a spreadsheet-based method to project battery gross capacities, motor, and battery power ratings, and battery costs for an array of future PEVs. In reference [31], the authors propose an ordered charging/discharging control strategy for EVs based on vehicle-to-vehicle (V2V) charging/discharging technology. Sun et al. [32] introduce a periodic fluid model to describe charging operations at a battery swap station and find an optimal battery purchasing and charging policy.

In addition, Pagany et al. [33] provide a comprehensive overview of the charging station (CS) models and find that almost all CS locating concepts are proposed for urban areas. The authors conclude that new and more integrated approaches should be developed in the next stage.

With the continuous improvement of battery endurance and the popularity of residential charging piles, large charging stations will mainly serve public transport, especially ETs. A very important issue that should be taken into consideration when planning an ET charging station is that the recharging time cost is more sensitive to a taxi driver than to a personal home-use EV. Therefore, we assumed that only fast charging piles are placed in an ET charging station in this study.

Because of the randomness on destination choice, the process of choosing the travel routes of ETs, which relates to the rationality of charging station siting, has no rules to follow.

This paper proposes an improved destination selection model to simulate taxi driving behavior based on dividing the target area into different districts. In different time periods, every district is given a unique rating and road congestion degree. The contributions of this paper can be summarized as follows:

1. The improved destination selection model can simulate the travel behavior of electric taxis well and has strong practical significance.
2. Compared to the traditional method (as shown in Appendix A), the improved destination selection model can reduce many calculations.
3. The statistical knowledge is used to find the right capacity of each charging station according to the actual operation data.

The paper is organized as follows. Area division and road congestion degree are presented in Section 2. Section 3 introduces the ET's operating model and the analysis of the model complexity. A case study is employed in Section 4 to demonstrate the performance of the proposed models. Conclusions are drawn in Section 5.

2. Hierarchical Structure of the Electric Taxi Target Area

The tax operating route is closely related to passenger demand, road conditions, etc. In this paper, the target area is subdivided into districts of the same size and sequentially numbered. According to the characteristics, districts are classified into different regions.

2.1. Road Congestion Degree

The road congestion degree is a quantitative description of the state of traffic congestion, which can be indicated through time, the consumption of oil, etc. The construct district road congestion degree index *Y* is defined as

$$Y_i = \alpha \times BD_i + \beta \times SD_i + cont \tag{1}$$

where

BD_i: the rating of the region that contains district *i*;

SD_i: the rating of the public places that belong to district *i*;

α, β: weighting coefficient; and

$cont$: constant coefficient

According to the district road congestion degree *Y*, the districts are divided into four different levels, and each level has different access times and rates of electrical power consumption. Detailed classification is provided in Table 4 of Section 4.2.

2.2. District Rating

Every district is assigned its own district rating. The district rating is defined by the regional rating and the business purpose of the region, such as bars, large residential areas, shopping malls, railway stations, and scenic spots.

District ratings, region ratings and public place ratings are formulated as

$$rank_i = \sqrt{BD_i^{\,2} + \omega \times (SD_i)^2} \tag{2}$$

$$BD_i = K \times \sum\nolimits_U i_u + p \tag{3}$$

$$SD_i = \begin{cases} \prod\nolimits_R i_r \big/ \sum\nolimits_R i_r, & \text{if } N_R > 1 \\ i_r, & \text{else} \end{cases} \tag{4}$$

where

i: district number;

$rank_i$: the rating of district *i*;

BD_i: the rating of the region that contains district *i*;

SD_i: the rating of the public places that belong to district *i*;

K, ω: weighting coefficient;

U: the set of public places in the region that contains district *i*;

p: constant coefficient;

R: the set of public places in district *i*;

N_R: the number of elements in *R*; and

i_u, i_r: the corresponding rating values of public places.

Combining Equations (1)–(3), the district rating is as follows:

$$rank_i = \sqrt{(K \times \sum_U i_u + p)^2 + \omega \times (\prod\nolimits_R i_r \big/ \sum\nolimits_R i_r)^2} \tag{5}$$

3. Electric Taxis Operation Model

To describe the operation process in the ET operation model, we introduce the load factor, passenger destination selection rate, and empty driving destination selection rate to simulate the operation of an ET. In our model, the load factor helps to describe the busy degree of the ET charging station, and both the passenger destination selection rate and the empty driving destination selection rate help to the ETs decide their moving destination when there is passenger or no passenger on it.

3.1. Load Factor

In this paper, we assume that the consumer needs the ETs to follow a Poisson distribution and then:

$$\begin{cases} P(x) = m^x e^{-m} \big/ x! \\ m = \lambda t \\ \lambda = \alpha \times rank_i + \theta \end{cases} \tag{6}$$

where

$P(x)$: the rate of x passengers needing to take taxis during the counting period t;

t: counting period;

λ: the rate of average riding needs;

m: average number of consumers needing to take taxis during the counting period; and

α, θ: weighting coefficients

The probability of at least one passenger needing to take taxi in the counting period, namely, load factor (*ZP*), is

$$\begin{cases} ZP = P(x > 0) \\ P(x > 0) = 1 - P(0) \end{cases} \tag{7}$$

Combining Equations (6) and (7), we have

$$ZP = 1 - e^{-t \times (\alpha \times rank + \theta)} \tag{8}$$

3.2. ET Destination Selection Model When the ET Has Passengers

As there are so many destination choices, we first select a region and then select a district in the region as 'have passengers' for the ET's destination.

3.2.1. Region Selection Principle

By collecting the trip distribution of each region in different times, the number of passengers from the starting point to each region can be denoted as the 'attractive' value $P = [n_1, n_2, \cdots, n_m]$.

The target region of the ET's choice can be measured by the destination selection probability interval $I = [n_1 / \sum_m n_i, n_2 + n_1 / \sum_m n_i, \cdots, 1]$, which can be further carried out by the roulette select strategy.

3.2.2. District Selection Principle

Each district in the chosen region has a corresponding rating to help guide the ET's next moving behavior. Combining the distance from the starting district to destination (*L*), the 'attractive' value *Q* of each district is defined as Equation (9)

$$Q = \begin{cases} L/5(\tau L + \gamma \times rank_i + \delta), L < a \\ (b - L)/(\tau L + \gamma \times rank_i + \delta), a \le L < b \\ (c - L)/(10\tau L + \gamma \times rank_i + \delta), c > L \ge b \end{cases} \tag{9}$$

where

a denotes the shortest distance that passengers will consider taking a taxi;
b denotes the farthest distance that passengers will consider taking a taxi;
c denotes the farthest distance in the target area; and
τ, γ, δ denote corresponding weighting coefficients.

where *Q* is employed to construct a probability interval, and a roulette select strategy is employed to help decide the ET's target district.

The 'empty driving' ET will move towards a prosperous district that is closer and has larger travel demand, hoping to meet passengers in the shortest distance and amount of time.

Therefore, we define these districts with larger travel demand as 'attractive regions'. Then, the 'empty driving' ET destination selection is divided into two situations: outside and inside the attractive regions.

3.2.3. ET outside the Attractive Regions

We connect the starting district with each attractive region and calculate the distances *L*. The 'attractive' value function *W* is formulated as

$$\begin{cases} W = DQ / L \\ DQ = \sqrt{\sum_I rank_i^{\,2}} \end{cases} \tag{10}$$

where DQ denotes the rating of the attractive region and I denotes the set of districts in the attractive regions.

The selection on the destination of 'empty driving' ET that outside the attractive region can be carried out by the roulette selection strategy.

The destination selection of 'empty driving' ET outside the attractive region is shown in Figure 1. From Figure 1, we can find that the 'empty driving' ET is attracted by the 'region' first, and then the driver should decide which specific place in that region should be his/her target objective.

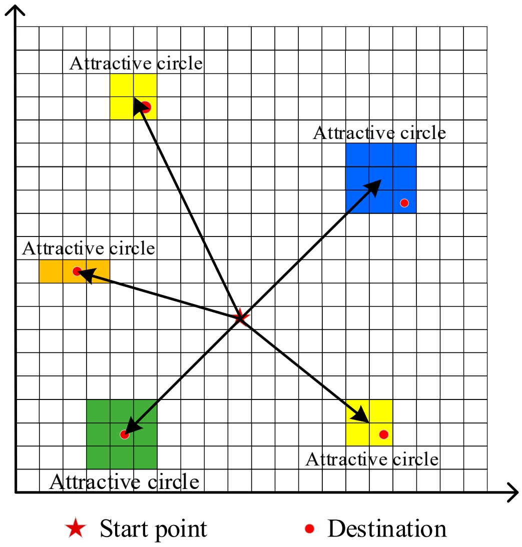

Figure 1. Destination selection of empty driving ET outside the attractive region.

3.2.4. ET inside the Attractive Region

When 'empty driving' ET is in the attractive region, drivers prefer to seek a surrounding district in the circle as the destination. Meanwhile, the road conditions of candidate destinations should be considered.

According to the logit model, the construct utility function (H_i) is

$$H_i = \theta_0 + \theta_1 rank_i + \theta_2 Y_i \tag{11}$$

where Y_i denotes road congestion degree of candidate district and $\theta_0, \theta_1, \theta_2$ denote weighting coefficients.

According to reference [34], Logit selective probability (P_i) is

$$\ln\left(\frac{P_i}{1-P_i}\right) = -\ln\left(\sum_{j=1}^{N} e^{H_j}\right), j \neq i \tag{12}$$

where N denotes the number of candidate districts in the attractive region.

Selection of the destination during 'empty driving' ET inside the attractive region can also be carried out by the roulette strategy.

3.3. ET's Operating Model

Based on the submodel we introduced above, we can build a simulation ET operation system to describe the ET driving and charging behavior with a four-mode ET operation model, which can be defined as 'have passengers', 'empty driving', 'charging', and 'idle' submodels.

3.3.1. Model Assumptions

1. Vehicles only operate for M hours, and all are fully charged when the day's work starts;

2. Each ET has a corresponding 'trigger time' T_b and 'ending time', in this paper, the time is in minutes, so, $T_e = T_b + T_M \times 60$; when $t = T_b$, taxis begin operating, and when $t = T_e$, taxis finish operating, T_M is maximum business/running time for an ET.
3. Information on each ET includes the following: 'trigger time' T_b, 'ending time' T_e, current power L_f, current area I, moving route R, district conversion time T_s, power consumption L, and vehicle status S. Status is updated per K minutes.
4. The ET's route is the straightest line that connects the starting district and destination district.
5. 'Empty driving' ETs determine whether they take passengers by the load factor when passing each district.
6. If the 'have passengers' ET cannot reach the nearest charging station after it reaches its destination, the ET rejects any passengers and moves to the nearest station for charging.
7. If the 'empty driving' ET cannot reach the nearest charging station after it reaches its destination, the ET changes its route and moves to the nearest charging station.

3.3.2. Detailed Steps

Step 0: Initialize the information of each ET $x_i = [T_b, T_e, L_f, I, R, T_s, L, S]$; the vehicle status is changed to 'idle';

Step 1: If $t \in [T_b, T_e]$, ET operates, go to Step 2; otherwise, go to Step 7;

Step 2: (status update)

(1) If $T_s(a+1) > t \geq T_s(a)$, update the information: $L_f = L_f - L(a)$, $I = R(a)$, $a = a+1$, (if $R(a)$ is the destination, the vehicle status is changed to 'empty driving'); go to Step 3;

(2) If $T_s(a) > t$, go to Step 7;

Step 3: (status judgment)

(1) If the vehicle status is 'have passengers', skip to Step 7;

(2) If the vehicle status is 'idle', $a = 1$, determine whether to take passengers by the passenger load factor. If passengers are taken, go to Step 4; otherwise, go to Step 5;

(3) If the vehicle status is 'charging', determine whether to take passengers by the passenger load factor. If passengers are taken, go to Step 4; otherwise, go to Step 7;

(4) If the vehicle status is 'empty driving', determine whether to take passengers by the passenger load factor. If ET takes passengers, go to Step 4; otherwise, determine the route $C = [v_1, v_2, \ldots, v_s]$ and power consumption $L_c = [l_{v_1}, l_{v_2}, \ldots, l_{v_s}]$ from the next district *k* to the nearest charging station. If $L_f - l_k - \sum_s l_{v_i} \geq 0$, this means the 'empty driving' ET has enough power to keep the 'empty driving' state; go to Step 7. Otherwise, travel to the nearest charging station, where the vehicle status will be changed to 'charging', and go to Step 6.

Step 4: ('have passengers' mode)

Select the destination. Determine the route from the departure district to the destination $R = [r_1, r_2, \ldots, r_m]$, the route from the destination to the nearest charging station $C = [c_1, c_2, \ldots, c_x]$, and the power consumption for passing each district along the route $L_R = [l_{r_1}, l_{r_2}, \ldots, l_{r_m}]$, $L_C = [l_{c_1}, l_{c_2}, \ldots, l_{c_x}]$.

(1) If $L_f - \sum_m l_{r_i} - \sum_x l_{c_i} \geq 0$, this means the ET has enough power to drive passengers to the destination, so the ET takes passengers, and the vehicle status is changed to 'have passengers'. Determine the district conversion time $T_s = [t + t_{r_1}, t + t_{r_1} + t_{r_2}, \ldots, t + \sum_m t_{r_i}] = [T_{r_1}, T_{r_2}, \ldots, T_{r_m}]$ by the consuming time of passing each district $t_s = [t_{r_1}, t_{r_2}, \ldots, t_{r_m}]$, $a = 1$, and go to Step 7.

(2) If $L_f - \sum_m l_{r_i} - \sum_x l_{c_i} < 0$, this means the ET does not have enough power to drive passengers to the destination, so the ET rejects the passengers. If the vehicle status is 'idle' or 'empty driving',

the taxi travels to the nearest charging station, and the vehicle status is changed to 'charging'; go to Step 6. Otherwise, go to Step 7.

Step 5: ('empty driving' mode)

Select the 'empty driving' ET's destination. Determine the route $R=[r_1,r_2,....,r_e]$, power consumption of passing each district $L_R=[l_{r_1},l_{r_2},....,l_{r_e}]$ and district conversion time $T_s=[T_{r_1},T_{r_2},\cdots,T_{r_e}]$. Determine the route from district r_1 to charging station $C=[c_1,c_2,\cdots,c_u]$ and power consumption $L_C=[l_{c_1},l_{c_2},...,l_{c_u}]$. If $L_f-l_{r_1}-\sum_u l_{c_i}\ge 0$, this means the ET has enough power in the 'empty driving' state, so the vehicle status is changed to 'empty driving', $a=1$, go to Step 7. If $L_f-l_{r_1}-\sum_u l_{c_i}<0$, this means the ET does not have enough power in the 'empty driving' state, so the ET travels to the nearest charging station and charges. The vehicle status is changed to 'charging'; go to Step 6.

Step 6: ('charging' mode)

Determine the route of charging $R=[r_1,r_2,...,r_y]$, power consumption $L_R=[l_{r_1},l_{r_2},\cdots,l_{r_y}]$ and district conversion time $T_s=[T_{r_1},T_{r_2},\cdots,T_{r_y}]$, and go to Step 7.

Step 7: $t=t+1$, if $t\le\max(T_e)$, return to Step 1; otherwise, end the cycle.

The general flowchart of the whole paper is shown in Figure 2.

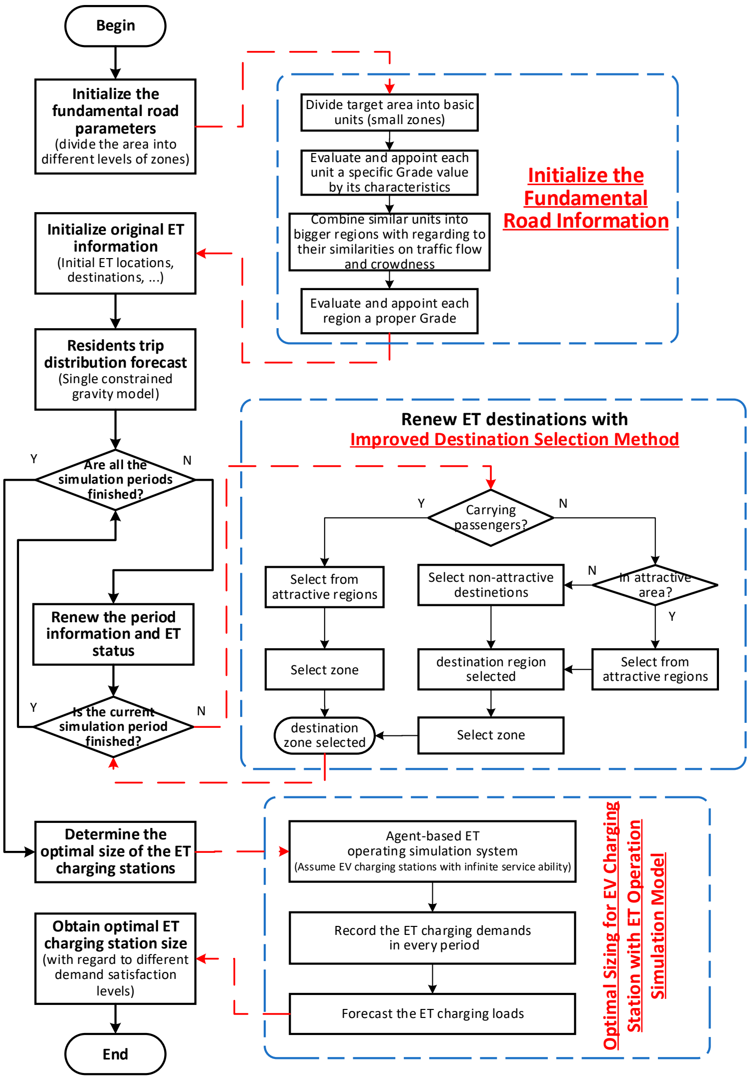

Figure 2. General flowchart of the whole paper.

3.4. Analysis of Complexity

The complexity of the ET operating model mainly reflects the destination choice, especially in the passenger destination choice. It needs to calculate the 'attraction' value of each district if the traditional method in the ET operating model is employed.

The complexity of the traditional method (C_1) and the improved method in this paper (C_2) are formulated as follows: the specific calculation process of Formula (13) and the brief introduction of traditional method is as depicted in Appendix A.

$$\begin{cases} C_1 = N(n_1(M-1)f_p + n_2 m_4 f_p) \\ C_2 = N(n_1(m_1 f_p + m_2 f_p) + n_3 m_3 f_p + n_4 m_4 f_p) \\ \eta = 1 - C_2/C_1 \end{cases} \tag{13}$$

where

N denotes the number of ETs;

M denotes the number of all districts; $M = m_1 \times m_2$

m_1 denotes the number of regions;

m_2 denotes the number of districts in one region;

m_3 denotes the number of attractive regions;

m_4 denotes the number of surrounding districts;

n_1 denotes the number of target districts chosen when the ET 'has passengers';

n_2 denotes the number of target districts chosen when the ET is 'empty driving'; $n_2 = n_3 + n_4$

n_3 denotes the number of target districts chosen when the 'empty driving' ET is outside attractive regions;

n_4 denotes the number of target districts chosen when the 'empty driving' ET is inside attractive regions;

f_p denotes the calculated cost of one ET making one probability selection; and

η denotes the rate of calculated cost reduction.

To evaluate the performance improvement of our work, a case study with the following $m_3 = m_1/2$ parameters setting is employed in this study, where $m_4 = 8$, $f_p = 1$, $N = 1$, $n_1 = 1$, $n_2 = 2$, and $n_3 = n_4 = 1$. A comparison study on the destination selection estimation cost reduction is presented in Table 1 and Figure 3.

Table 1. Comparison study on the destination selection estimation cost reduction.

M	**10.0**	**100.0**	**200.0**	**500.0**	**1000.0**
m_1	2.0	10.0	10.0	20.0	20.0
m_2	5.0	10.0	20.0	25.0	50.0
C_1	25.0	115.0	215.0	515.0	1015.0
C_2	16.0	33.0	43.0	63.0	88.0
η (%)	36.0	71.3	80.0	87.8	91.3

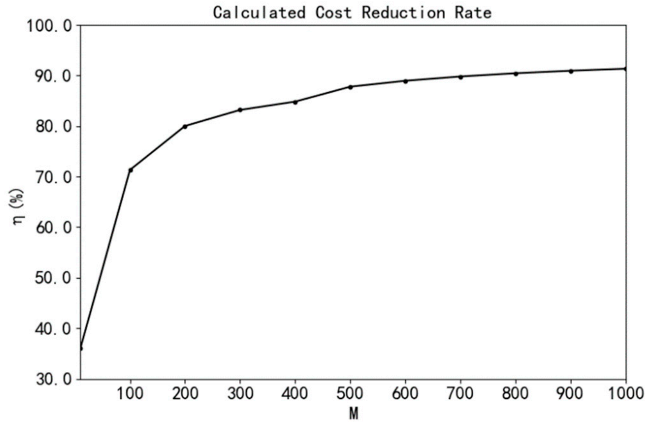

Figure 3. Calculated cost reduction rate with regard to increased model precision.

Figure 3 shows that the calculation cost of the model is reduced dramatically with increasing district number and ET number. This means that when the simulation precision of the system is promoted quickly, the calculation cost reduction benefits from the model we proposed compared with the former existing model.

4. Case Study

4.1. Problem Description

To verify the effectiveness of the algorithm proposed in this paper, a case study that comes from the city of Beijing, China, is employed for demonstration. Beijing is one of the cities that first promoted electric vehicles. To date, the city has had more than 1000 ETs and has built more than 10 charging stations.

In this paper, the target area is divided into many districts that are sequentially assigned numbers. The whole area is divided into 20 major regions (each region is five districts long and four districts wide). The area has 10 charging stations, as shown in Figure 4. And Table 2 has shown the regional information in detail.

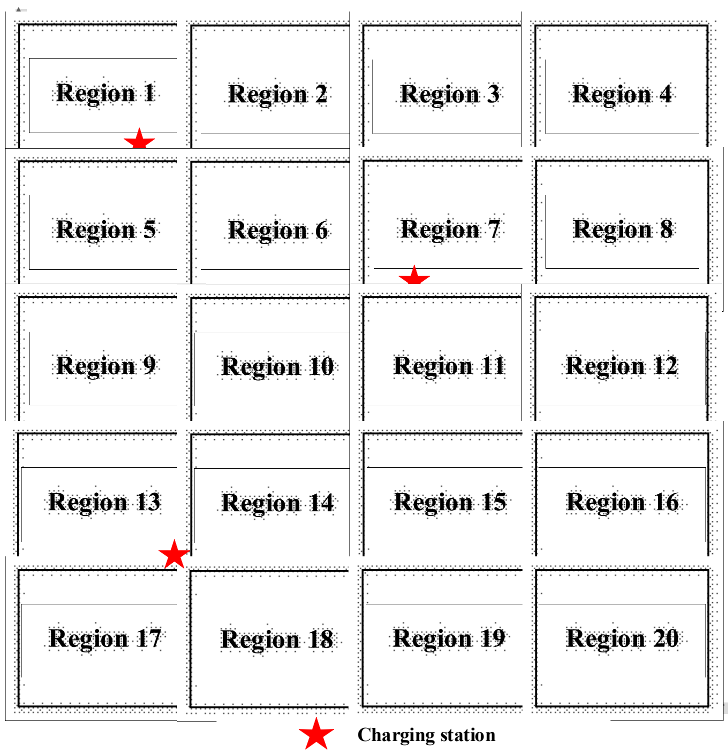

Figure 4. Area division and locations of stations.

Table 2. Regional information.

Subject	District Number
Existing station	38, 51, 64, 152, 167, 182, 217, 271, 305, 336
Mall	47, 56, 62, 65, 86, 99, 108, 124, 134, 157, 163, 170, 184, 187, 190, 196, 197, 205, 208, 234, 238, 248, 321, 369
Wholesale market	127, 158, 168, 254, 261, 278, 339, 353, 374, 384
Bar	88, 132, 156, 176, 234
Residential area	14, 15, 20, 33, 38, 39, 60, 102, 122, 146, 285, 297, 304, 319, 328, 329, 336, 343, 344, 362
Station	108, 215, 220, 245, 291, 310, 333, 352
Scenic spot	94, 106, 131, 165, 172, 192, 273
Office area	2, 3, 6, 11, 22, 23, 29, 42, 71, 86, 97, 104, 105, 108, 115, 135, 136, 156, 157, 164, 177, 179, 182, 188, 197, 203, 226, 229, 243, 247, 257, 258

4.2. Case Parameters Setting

The data in this paper are Beijing real-time data obtained using Baidu map statistics. (http://lbsyun.baidu.com/)

One day is divided into four periods: 7:00–10:00, 10:00–18:00, 18:00–22:00, and 22:00–7:00. The level values of public places are as follows (shown as Table 3).

Table 3. Rank of public place.

Subject	7:00–10:00	10:00–18:00	18:00–22:00	22:00–7:00
Mall	2	3	4	1
Station	3	5	3	2
Office area	4	5	4	2
Bar	1	1	1	4
Wholesale market	1	5	3	1
Residential area	4	3	4	2
Scenic spot	2	4	2	1

Road congestion degrees are classified as follows (shown as Table 4).

Table 4. Road congestion degrees.

Traffic Rank	I	II	III	IV
Rank Index	>70	50–70	30–50	<30
Time	15 min	8 min	4 min	2 min
Electricity consuming	2 kWh	1.8 kWh	1.5 kWh	1.2 kWh

Through data collection, the travel distributions of large areas in each period are obtained, such as region 1 in the 7:00–10:00 period:

As shown in Table 5, the time residents in region 1 choose region 6 as the destination is 132 of 1000 trips. The probability of choosing region 6 is 0.132; no one goes to region 20, so the probability is 0.

Table 5. Region 1 trip distribution.

Destination	Times	Destination	Times
1	68	11	57
2	42	12	24
3	128	13	9
4	62	14	5
5	128	15	3
6	132	16	2
7	91	17	1
8	57	18	0
9	99	19	0
10	92	20	0

Combined with the statistics of resident travel, the weight coefficients of Formula (4) are set at $\omega = 4$, $K = 0.5$, and the constant p is 2. Through the taxi driving statistics, the road congestion degree weight coefficients of Formula (5) are set at $\alpha = 3$, $\beta = 8$, and the constant $cont$ is 5. The load factor weight coefficients of Formula (8) are set at $\alpha = 0.0275$ and $\theta = 0.0891$ by using the least squares method to curve fitting of passenger statistics, and the fitting error is close to 0. The parameters of Formula (9) are set at $a = 3$, $b = 15$, $c = 40$, $\tau = 0.6$, $\gamma = 0.8$, and $\delta = 0.3$. When 'empty driving' ETs are in the attractive regions, the weight coefficients of Formula (12) are set at $\theta_0 = -0.95$, $\theta_1 = -0.21$, and $\theta_2 = 0.05$ to analyze the 'empty driving' statistical data.

The 'empty driving' attractive regions are listed in Table 6.

Table 6. Empty driving attractive regions.

Period	District Number
7:00–10:00	18, 19, 20, 38, 39, 40, 58, 59, 60, 101, 102, 103, 121, 122, 123, 141, 142, 143, 308, 309, 310, 328, 329, 330, 348, 349, 350, 322, 323, 324, 342, 343, 344, 362, 363, 364, 336, 337, 338, 356, 357, 358, 376, 377, 378
10:00–18:00	2, 3, 4, 22, 23, 24, 42, 43, 44, 8, 9, 10, 28, 29, 30, 48, 49, 50, 115, 116, 117, 135, 136, 137, 155, 156, 157, 175, 176, 177, 195, 196, 197, 162, 63, 164, 182, 183, 184, 202, 203, 204, 206, 207, 208, 226, 227, 228, 246, 247, 248
18:00–22:00	46, 47, 48, 66, 67, 68, 86, 87, 88, 164, 165, 166, 184, 185, 186, 204, 205, 206, 236, 237, 238, 256, 257, 258, 276, 277, 278, 290, 291, 292, 310, 311, 312, 330, 331, 332
22:00–7:00	87, 88, 89, 107, 108, 109, 127, 128, 129, 134, 135, 136, 154, 155, 156, 174, 175, 176

The geographical allocation of the regions is shown in Figure 5.

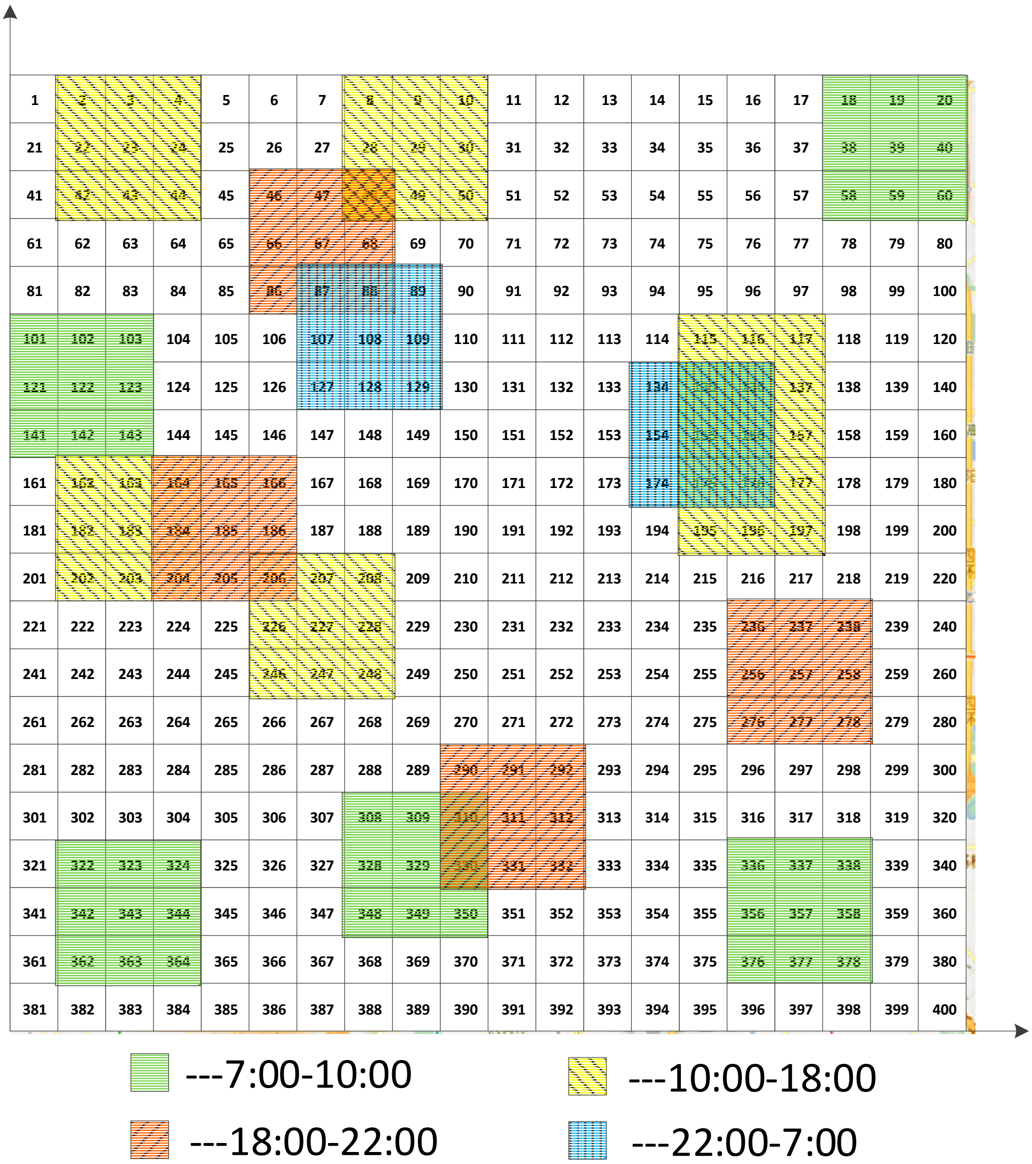

Figure 5. Empty driving attractive regions.

4.3. Algorithm Parameters Setting

The parameters of the algorithm setting are set as follows:

Maximum Iterations: 500;
The Number of ETs: 1000;
Maximum Business/Running Time for an ET: 5 h;
Maximum ET Travel Mileage: 260 km; and
ET Charging Time: 30 min.

4.4. Case Result

(1) The actual operating data of each charging station are shown in Figures 6–8.

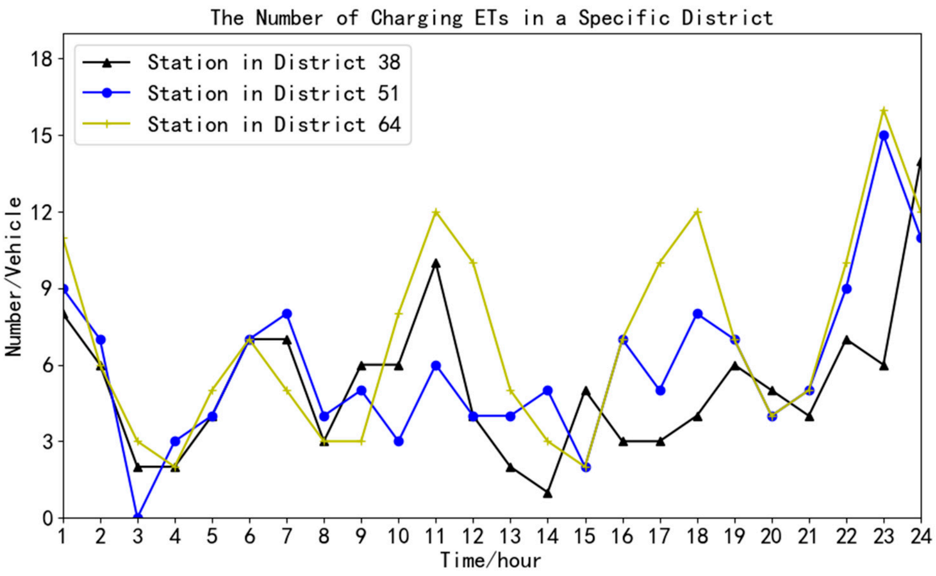

Figure 6. Forecast loads of the charging stations in Districts 38, 51, and 64.

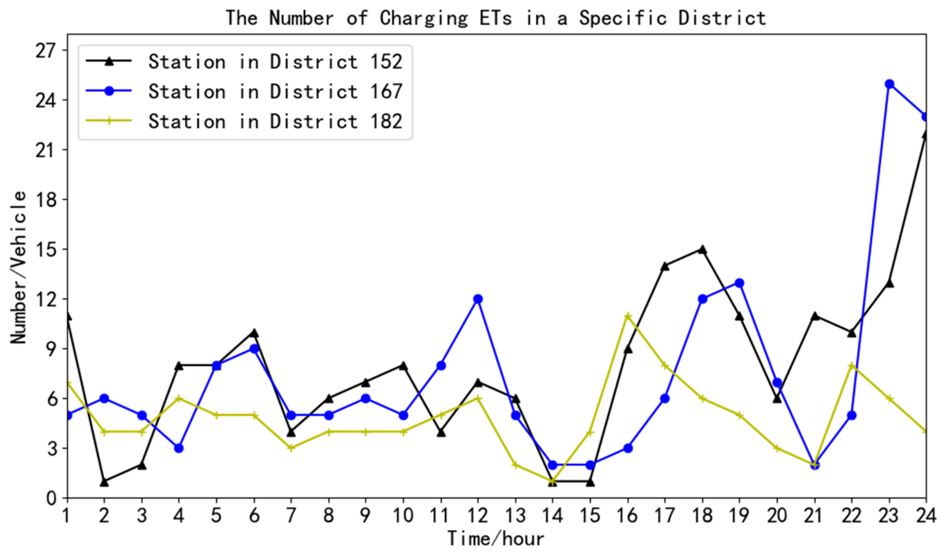

Figure 7. Forecast loads of the charging stations in Districts 152, 167, and 182.

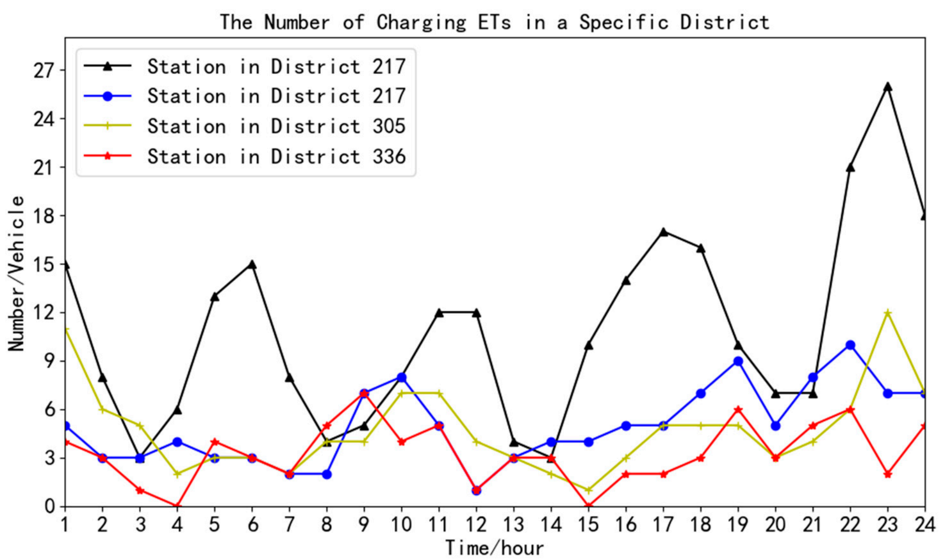

Figure 8. Forecast loads of the charging stations in Districts 217, 271, 305, and 336.

(2) The daily charging data of the charging station are fit with the normal distribution and the Poisson distribution.

The result of the charging station in district 305 is shown in Figure 9. The specific results of the ten charging stations are shown in Appendix B.

Table 7 shows the detailed deployment plan for each charging station under different confidence intervals.

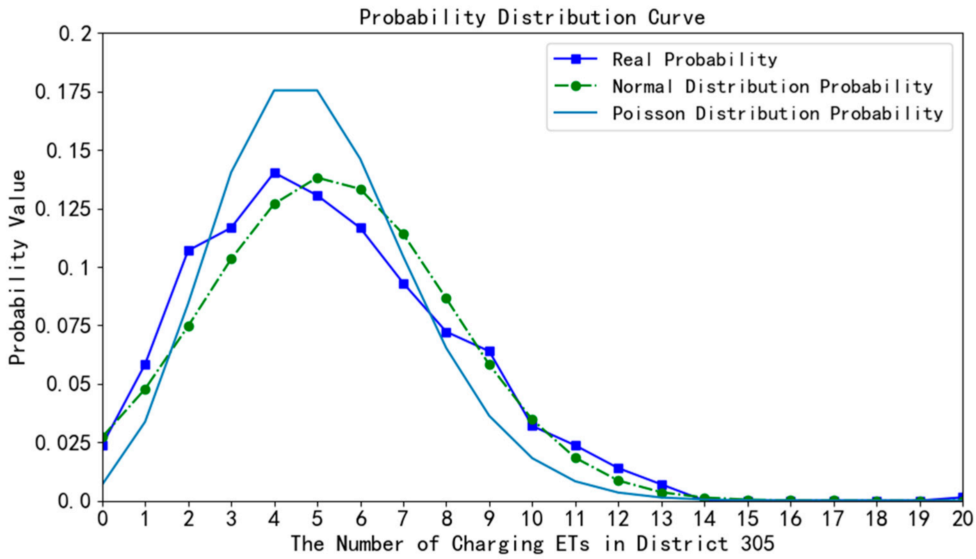

Figure 9. Statistical data of the charging station in District 305.

Table 7. Charging station deployment plan.

Charging Station District	**Charging Station Deployment**			
	Normal Distribution		**Poisson Distribution**	
	95% Confidence Interval	**85% Confidence Interval**	**95% Confidence Interval**	**85% Confidence Interval**
38	11	10	9	7
51	13	10	10	9
64	13	11	10	9
152	17	13	12	10
167	17	14	12	10
182	11	9	9	7
217	18	15	14	12
271	11	9	9	7
305	10	9	9	7
336	8	6	6	5

As shown in Table 7, taking the charging station in district 305 as an example, under a 95% confidence interval, if we use a normal distribution, the number of properly installed charging devices in the charging station should be 10.

5. Conclusions

In this paper, we propose an improved destination selection model to simulate the ET operation system. This model helps us predict the ETs' charging demand. Then, statistical analysis is employed to find the optimal ET charging station size.

The main contributions of this paper are as follows:

(1) The logit model was previously used in research related to geography and population. In this paper, it is used in the driver's destination selection, which has strong practical significance.
(2) Compared to the traditional method in Appendix B, the method we proposed in this paper can reduce calculation cost better based upon a greater extent of the division of the area.
(3) With the help of statistical knowledge, we can give the proper number of charging devices in every station under different confidence intervals.
(4) Based on the Beijing real-time data obtained using Baidu map statistics to verify the method proposed in this paper, the result has good practicability.

Author Contributions: R.S. is one of the funding acquisitions and is also the contributor to construct the conceptual and basic model of the work, supervise and participate in writing the paper; J.L. is the contributor to construct the model in detail and is also to carry out the algorithm program and collect the data; Z.L. is the contributor to collect the case study data, revise the algorithm and finish part of the original manuscript; L.N. is the contributor to investigate the data of the case study, and also help to verify and validate the result of the algorithm; E.I. is the contributor to advise further improving the performance of the algorithm, and validate the effectiveness of the method proposed in this work; F.F. is the corresponding author, one of the funding acquisitions and is also the conceptual contributor to the model, communicate and coordinate with all the other authors.

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Conflicts of Interest:The authors declared that they have no conflicts of interest to this work.

Appendix A

Assume the area divided into M districts, m_1 regions, every region has m_2 districts, and the attractive region has m_3 districts.

The traditional method of 'have passenger' that ETs use to choose a destination is to use roulette directly based on real statistics data, so the calculation cost of one 'have passenger' ET make n_1 choices is

$$\mathrm{cost}_p = n_1(M-1)\bullet f \tag{A1}$$

However, the traditional method of 'empty driving' that ETs use to choose a destination is to use roulette directly based on real statistics data in the surrounding area, so the calculation cost of one 'empty driving' ET make n_2 choices is

$$\mathrm{cost}_E = n_2 \bullet m_4 \bullet f,\ \ m_4 = 8 \tag{A2}$$

If the method proposed in this paper is adopted, then the calculation cost of one 'have passenger' ET to make n_1 choices is

$$\mathrm{cost}_p = n_1 \bullet (m_1 f + m_2 f) \tag{A3}$$

The calculation cost of one 'empty driving' ET to make n_3 choices when it is outside the attractive region and to make n_4 choices when it is inside the attractive region is ($n_2 = n_3 + n_4$)

$$\mathrm{cost}_E = n_3 \bullet m_3 \bullet f + n_4 \bullet m_4 \bullet f \tag{A4}$$

Appendix B

The specific results of the 10 electric charging stations are shown below:

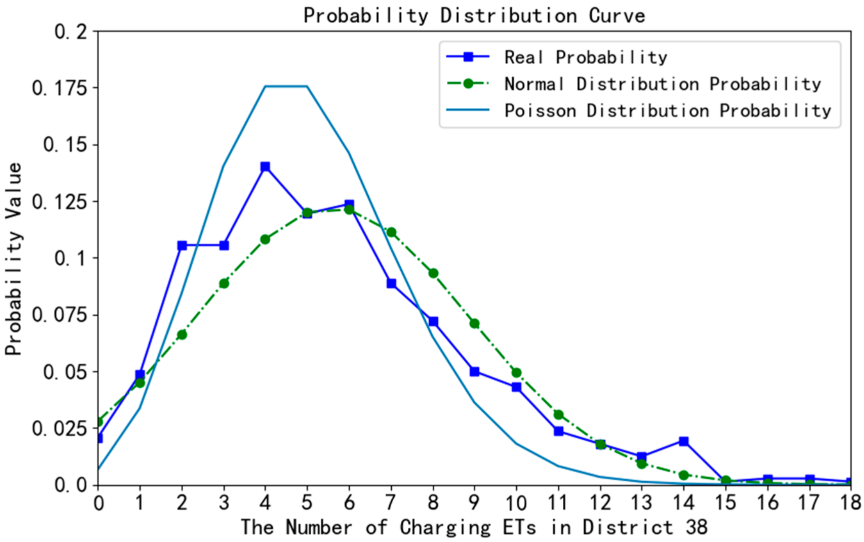

Figure A1. Statistical data of the charging station in District 38.

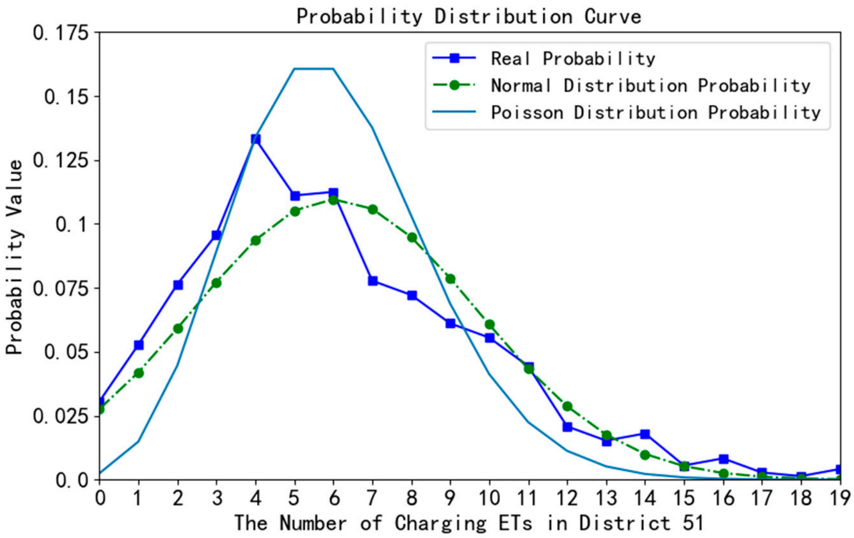

Figure A2. Statistical data of the charging station in District 51.

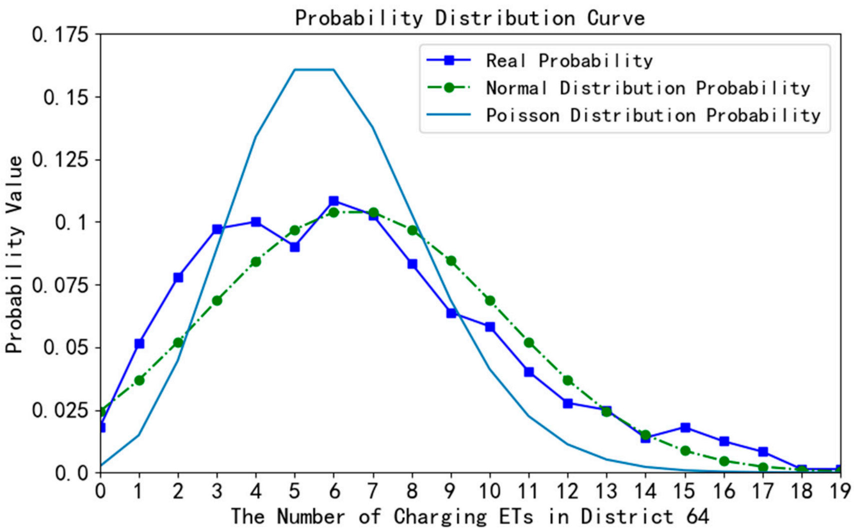

Figure A3. Statistical data of the charging station in District 64.

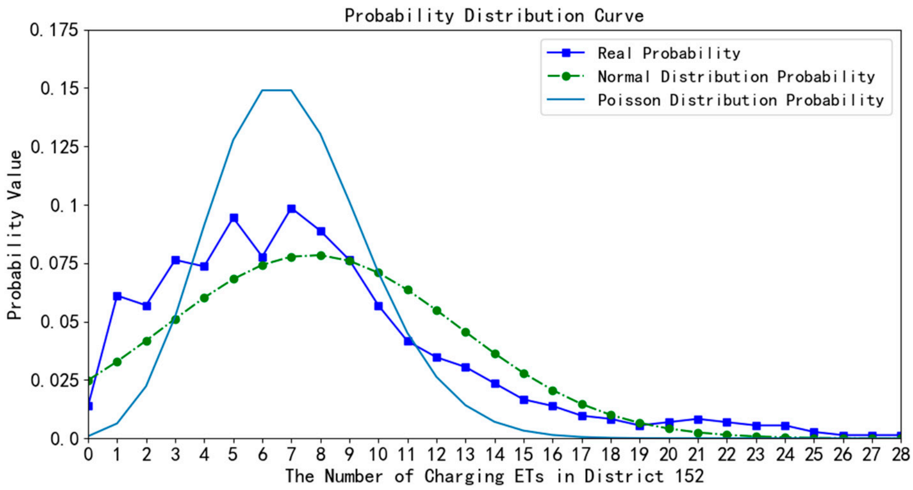

Figure A4. Statistical data of the charging station in District 152.

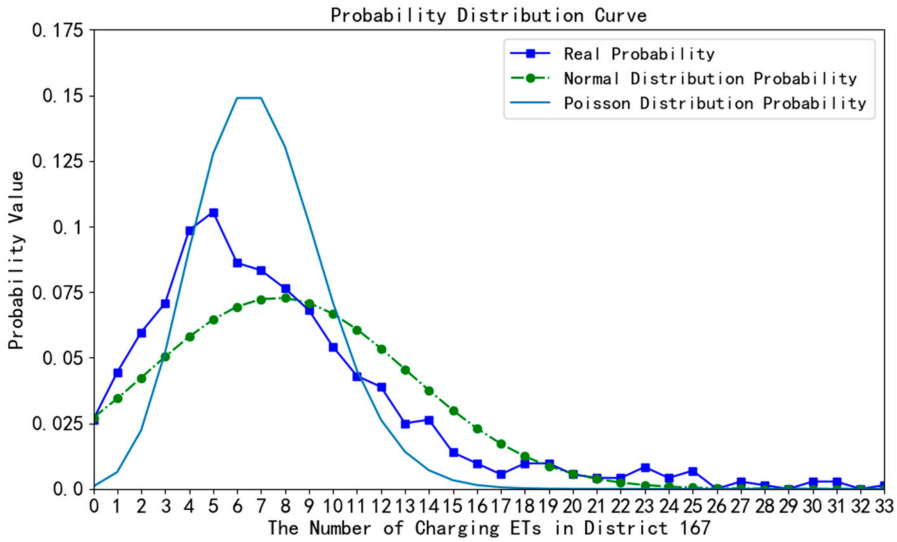

Figure A5. Statistical data of the charging station in District 167.

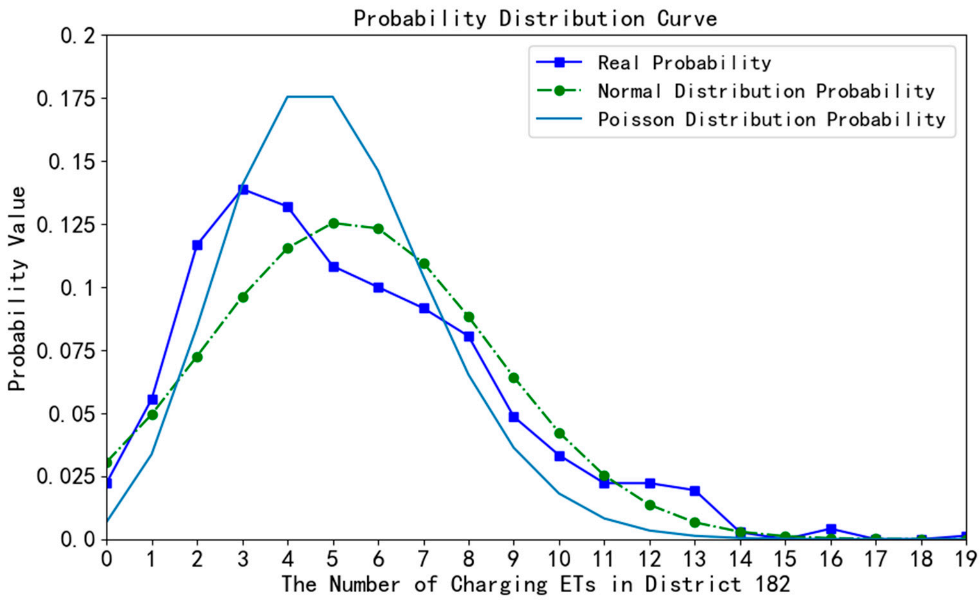

Figure A6. Statistical data of the charging station in District 182.

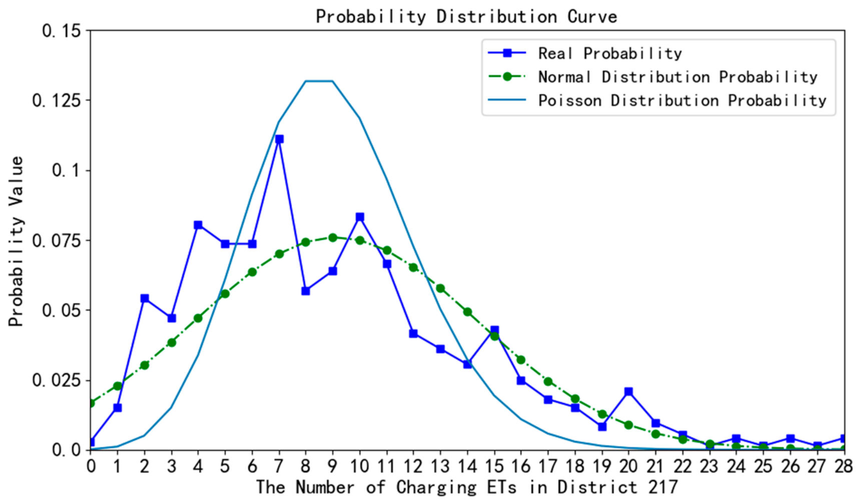

Figure A7. Statistical data of the charging station in District 217.

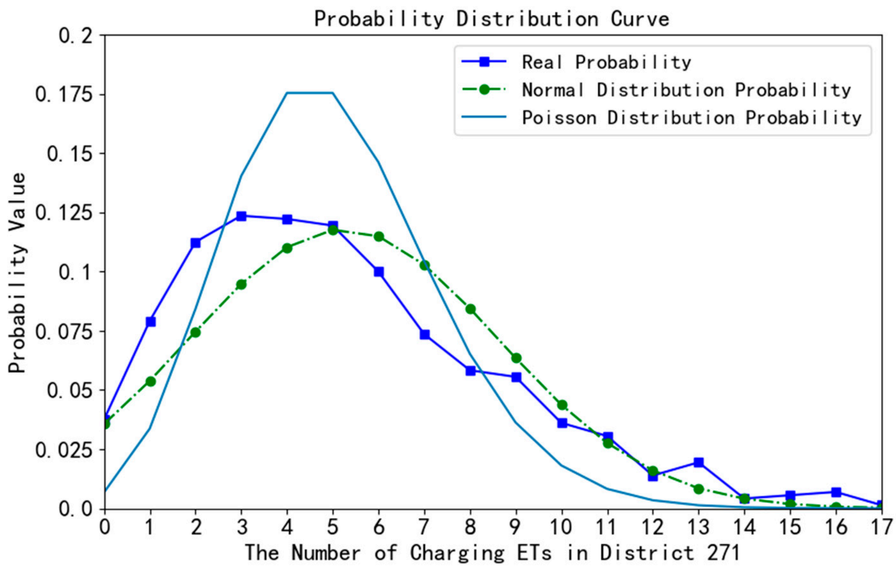

Figure A8. Statistical data of the charging station in District 271.

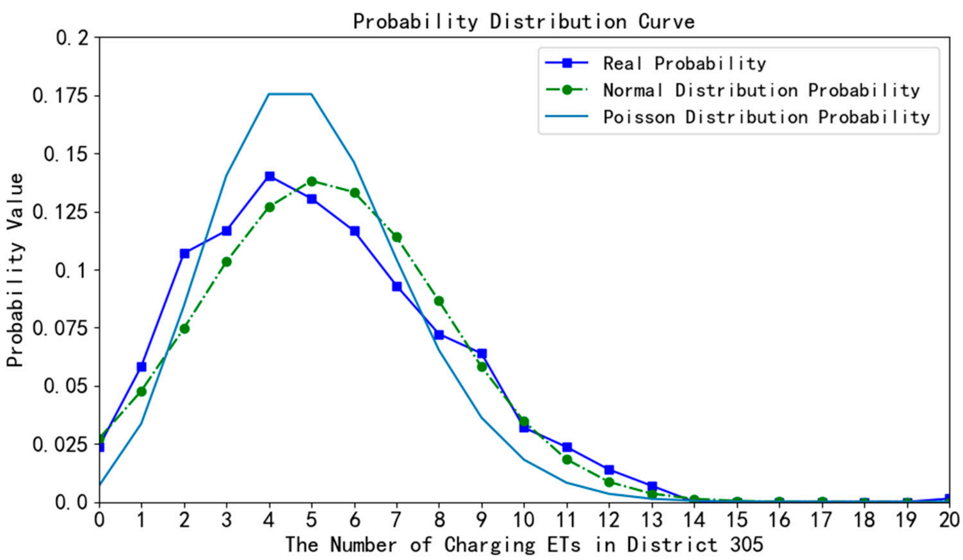

Figure A9. Statistical data of the charging station in District 305.

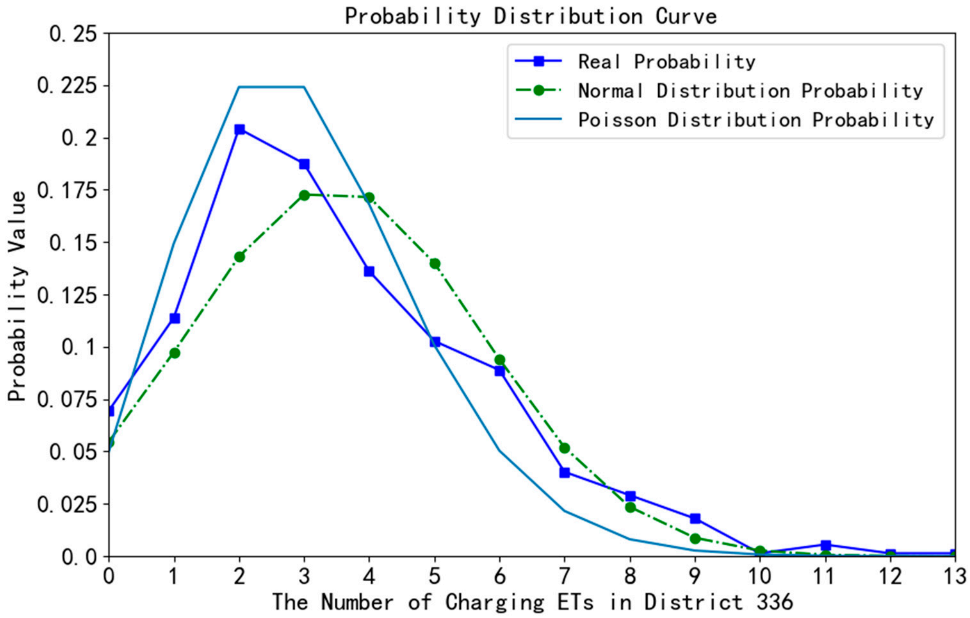

Figure A10. Statistical data of the charging station in District 336.

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