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Elastic Charging Service Fee Based Load Guiding Strategy for Fast Charging Station

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Abstract: Compared with the traditional slow charging loads, random integration of large scale fast charging loads will exert more serious impacts on the security of power network operation. Besides, to maximize social benefits, effective scheduling strategy guiding fast charging behaviors should be formulated rather than simply increasing infrastructure construction investments on the power grid. This paper has analyzed the charging users' various responses to the elastic charging service fee, introduced the index of charging balance degree to a target region by considering the influence of fast charging loads on power grid. Then, a multi-objective optimization model of the fast charging service fee is constructed, whose service fee can be further optimized by employing fuzzy programming method. Therefore, both users' satisfaction degree and the equilibrium of charging loads can be maintained simultaneously by guiding EVs to different fast charging stations reasonably. The simulation results demonstrate the effectiveness of proposed dynamic charging service pricing and the proposed fast charging load guidance strategy.

Keywords: EV; fast charging; real-time pricing; ordered charging; charging balance degree; Users' satisfaction; behavior characteristics; navigation strategy

0. Introduction

With the adjustment of global energy strategies, the energy transition and social comprehensive benefits generated by the industry of electric vehicles (EV) has attracted significant attentions. As the penetration rate of EVs increasing gradually, the traditional time-oriented slow-charging mode can hardly meet the urgent and efficient charging demands for myriad of EVs within a short time. Fast charging, a novel technology to replenish EVs in the short-run, is the future development orientation. However, the access of large-scale, disordered and random fast-charging loads will generate uncertainties in both time and space dimensions, which will exert unpredictable negative effects on the safe and stable operation of the grid [1-6]. Thus, the EVs' fast charging behaviors should be orderly coordinated.

The EV users' charging behaviors of charge location selection and path planning, etc. are mainly affected by factors in three aspects: the geographic location of charging stations, charging service fees, user types and their travel characteristics. Recent years have witnessed a lot of researches conducted by scholars concerning the price-guided orderly charging strategies. In [7], the optimization model where the objective to minimize the peak-valley slip ratio, and formulation of peak-valley time-of-use pricing were put forward to achieve the peak-load shifting. In [8], a multi-objective control method was proposed, which was based on time-of-use (TOU) price and regarded the minimal charging fees and the earliest initial charging time as the objective of two-stage control, and the effect of "peak-load shifting" and users' economical charging were achieved. In [9], the coordinated charging control method of EV charging stations were put forward based on dynamic TOU price, which reduced the operational cost and achieved "peak-load shifting" effect.

The above researches have effectively achieved coordinated charging's "peak-load shifting" effect toward the gird by regulating EV's initial charging time through "TOU price" and "peak-valley price" and have demonstrated the feasibility of guidance of charging behaviors by modulating charging service fee. However, the price above was still fixed and cannot be changed in real-time. In the future, the construction of charging stations will open the gate for the entrance social capitals. Under such circumstances, the power grid and charging stations will have decision-making ability of allowing their charging service fee to fluctuate within a reasonable range. On the other hand, the current research focuses mainly on the slow charging users, without considering their fast charging demands dispatching randomly along the road. Secondly, the guidance of charging service fee focuses primarily on regulating charging time, neglecting its effect on the space dimension, which leads to the imbalanced distribution of charging loads. Moreover, current research on the guidance effects of charging service fee based on "peak-valley price" only consider s the perspective of the safe operation of grid, while neglecting different types of users' response to the charging fees. Also, the calculation of users' own benefits needs to be improved.

In this paper, we first analyze the responses of different types of users toward the selection of charging location and charging service fee, and then we construct a multi-objective decision model based on the optimization goal of regional charging balance degree and user satisfaction. The intelligent algorithm is utilized to calculate the charging service fee at each fast charging station (FCS) in the target region. Finally, we verify the guidance effects of charging service fee and charging loads by using integrated simulation system of IEEE 33-node distribution network and its corresponding road network. The results demonstrate that, by regulating the charging service fees of different FCSs while ensuring the user satisfaction, EVs can be reasonably coordinated to every FCS, thus the charging loads are evenly distributed in the area.

1. Analysis of Charging Location Selection and Charging Service Fee Response Based on User Classification

1.1. Standard Classification of EV Fast Charging Users' Charging Location

The initial charging time and the selection of charging location vary with different EV users. And the initial time of fast charging cannot be arbitrarily changed due to urgent need and rigid demand of charging time. Therefore, this section will mainly focus on the selection criteria of charging location.

At present, the research on Intelligent Transport System (ITS) has been developed dramatically [10], which has been able to estimate the time to reach target location by considering the traffic flow. In the future, with the integration with the intelligent charging navigation system, by using the ITS, every travelling EV user can not only estimate in real-time the reaching hours to FCSs, but also get access to the occupancy rate at each FCS based on the current dynamic traffic flow.

Based on such tendency, assumed that all users are rational and there can be difference among the charging service fees for each FCS. The EV users' choices for FCS can be generally divided into three categories under the condition that the remaining State of Charge (SOC) is enough to reach destination:

- In the absence of ITS, users will choose the nearest FCS;
- With the access to ITS, the cost-insensitive users' general choice will be the FCS where they can finish the charging process in the shortest time;
- With the access to ITS, the cost-sensitive users will generally consider both the charging time and charging cost. When the charging time is within the affordable range, their priority will be the one where the charging cost is relatively low.

When the charging demand is generated, the total charging time can be expressed as equation (1):

$$T_d = T_a + T_q + T_c, \tag{1}$$

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where T_d is the total charging time (hours); T_a is the arrival time (hours), namely the time needed to travel to the FCS; T_q is the queuing time (hours), and the detailed deduction is in the Appendix B; T_c is the charging time (hours) - the time from the start of charging to the end of charging.

The overall charging cost is shown in equation (2):

$$C_d = C_a + C_s = C_t + C_c + C_s \, , \tag{2}$$

where C_d is the total charging cost (CNY); C_a is the arrival charging cost (CNY), that is, the charging cost when the vehicle reaches charging station considering the electricity consumption during the driving process. C_s is the cost of charging service fee (CNY); C_t is the cost of travel (CNY), which is the charging cost of the amount of electricity consumed by the vehicle in the process of traveling to the corresponding fast charge station; C_c is the charging cost (CNY) in the charging station.

According to the above user classification, the selection of charging location for Class I users and Class II users depends on the location of the vehicle, the road traffic condition and the charging waiting time. The charging behaviors for these two types of users is difficult to be altered by merely adjusting charging service fee. The Class III users are sensitive to the price, so their charging behaviors can be guided by setting different charging price or charging service fee for different FCSs.

Assuming that all charging stations participate in the grid dispatch of charging service fee, because the grid can constrain the operational cost of charging stations by adjusting the selling price to them. In the process, charging stations receive benefits from the grid, and they can reimburse some part of the rebates to the users. Therefore, this paper assumes that all charging stations satisfy the price-setting adjustment strategy of charging service fee of the grid.

1.2 User Charging Location Selection Probability Based on MNL Model

Firstly, the user proportion of adopting different charging location selection strategies has to be determined, i.e., we need to determine the probability of each strategy that EV users will employ in selecting charging location as mentioned in Section 1.1. Since nowadays the EV penetration rate is relative low, ITS is in theoretical stage, and the relevant statistical data is insufficient, this paper adopts the Multinomial Logit Model (MNL) [11], and obtain the actual distribution of various types of user through questionnaires, thus determining the users' selection probability.

The MNL is a probabilistic selection model that has been widely used in traffic demand side management strategies [11-12], and it is particularly suitable for predicting user's travel behavior. Naturally, this model can also be employed for the prediction of decision-making process concerning the selections of charging location.

According to the MNL, let P_i be the probability for i-th selection criteria of charging location. For the I, II and III charging location selection criteria described in Section 1.1, the probability are P_I, P_{II} and P_{III} respectively, where the P_I can be obtained directly by calculating the probability of installing ITS. If Class III is viewed as a reference, P_{II} can be described according to Logistic formula :

$$\ln(\frac{P_i}{P_{III}}) = \alpha^i + \sum_{k=1}^{K} \beta_k^i x_k^i \quad (i = II) \, , \tag{3}$$

where i is the selection criteria except for Class II users; α_i is the constant term for i-th option; x_k^i is k-th variable of i-th option is used; β_k^i is the corresponding coefficient of x_k^i.

It can be derived from (3) that

$$\begin{cases} p_I = p_{ITS} \\ p_{II} = \dfrac{e^{\alpha^2 + \sum_{k=1}^{k} \beta_k^2 x_k^2}}{1 + e^{\alpha^2 + \sum_{k=1}^{k} \beta_k^2 x_k^2}} \cdot (1 - p_{ITS}) \\ p_{III} = \dfrac{1}{1 + e^{\alpha^2 + \sum_{k=1}^{k} \beta_k^2 x_k^2}} \cdot (1 - p_{ITS}) \end{cases} , \tag{4}$$

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In order to obtain the probability of the users' adopting different types of criteria, the MNL model was calibrated by analyzing targeted statistical data, adopting data analysis software such as SPSS, and using polynomial Logistic regression to calculate constant α and the corresponding coefficient β of variables. However, due to the lack of relevant statistical data, it is necessary to collect samples. We set the personal attributes of EV users and the vehicle attributes as variables for charging location selection criteria, we made a summary table as shown in Table 1. Through sufficient data collection and the regression analysis of the sample statistics to get MNL model parameters, if knowing the owner' sex, age and vehicle type, the probability of adopting different selection criteria can be obtained.

Table 1. Standard statistics summary table for fast charging location selection of EV users.

EV users' personal attributes and vehicle types		Is ITS installed?	Cost per unit charge(CNY/kWh)		Affordable charging time range	
			Maximum affordability	Charging option change price	Remaining capacity(%)	Maximum charging time(h)
Gender	male					
	female					
Age	youth (18~38)					
	middle-aged (38~58)					
	elder (>58)					
EV type	small car					
	middle-large car					
	small SUV					
	middle-large SUV					
	others					

1.3 Cost-sensitive User's Response to Charging Service Fee

Since the charging behaviors of Type I, II users are irrelevant with charging service fee, we will not discuss such cases in detail. For the type III users who are sensitive to the cost, for them, it is necessary to balance the total charging time and total charging cost, and finally come to the decision of optimal charging location for their own needs. Rational users will always pursue benefit maximization, so this paper analyzes this type of user by using the weighted decision model, and their charging location decision can be described as:

$$\begin{aligned} X_{Ws} &= \min\left\{X_{Wi} \middle| i=1,2,\cdots,n\right\} \\ &= \min\left\{\omega_T X_{Ti} + \omega_C X_{Ci} \middle| i=1,2,\cdots,n\right\}' \end{aligned} \tag{5}$$

where X_{Ws} is the weighted attribute value of s-th scheme chosen by the user after the trade-off; X_{Wi} is the weighted attribute value of i-th scheme; X_{Ti} is the total charging time attribute value of i-th scheme; ω_T is the weight of time attribute; X_{Ci} is the total charging cost of i-th scheme; ω_C is the weight of cost attribute; n is the number of options for EV users.

Time and cost are two different dimensional, irrelevant attributes, so it is hard to directly weigh them. Considering that weighted attribute value X_{Wi} makes sense only when the schemes are compared, the enlargement and shrinkage of X_{Wi} will not affect the decision result. Therefore, the X_{Wi} time will be changed as the cost of time shown in equation (6):

$$X_{Wi}{}' = \frac{X_{Wi}}{\omega_C} = \left(\frac{\omega_T}{\omega_C}\right) X_{Ti} + X_{Ci} = \alpha X_{Ti} + X_{Ci}, \tag{6}$$

where α is the unit time value (CNY / hour); αX_{Ti} is time cost (CNY).

For EV users, the cost of time in the entire fast charging process means the time from the time when demand is generated to that the charging process is finished. And the key to determining the cost of time lies in the quantification of unit time value.

In present days, the time value for travelers is mainly determined by production method, income method [13], etc. The former is under the assumption that traveler's travel time is used for production, the increment is to be made as national income or national production value. This method is used for assessing the working time value. The latter is targeted for the traveler itself, the value of time is measured according to certain percentage (time value coefficient) of traveler's income. This method is generally used for assessing the leisure time value.

Here, the income method is used to quantify the cost of time. And the formula is:

$$\alpha_L = k\frac{P_p}{T_p}, \tag{7}$$

where α_L is the unit travel time value corresponding to leisure time (CNY/hour); k is the time value coefficient; P_p is laborers' annual income (CNY); T_p is laborers' annual working time (hours).

The time value coefficient in income method is closely related to the national economic level, which is set as 20-25% by UK scholars, and is advised to be set as 25% by French research report. Due to Chinese market economy construction, the wage distribution system is incomplete, some Chinese scholars believe that it should be set as 50% [14].

When users judge among these schemes, they actually compare the difference among the weighted attribute values. Take case i and case j for instance, according to the formula (6), there are:

$$\begin{aligned} \Delta X_W{}' &= X_{Wi}{}' - X_{Wj}{}' \\ &= (\alpha X_{Ti} + X_{Ci}) - (\alpha X_{Tj} + X_{Cj}) \\ &= \alpha(X_{Ti} - X_{Tj}) + (\delta_{se} + \delta_{si}) C_{cap}(1 - SOC_i) \\ &\quad - (\delta_{se} + \delta_{sj}) C_{cap}(1 - SOC_j) \\ &\approx \alpha(X_{Ti} - X_{Tj}) + (\delta_{se} + \delta_{si}) C_{cap}(1 - SOC) \end{aligned}, \tag{8}$$

where δ_{se} is the unit price (CNY/kWh); δ_{si}, δ_{sj} is charging service fee of the fast charge station i and j respectively (CNY / kWh); C_{cap} is the battery capacity of vehicle (kWh).

When the difference $\Delta X_W{}'$ is greater than zero, j-th scheme is the best solution. Otherwise, i-th scheme is better.

As can be seen from equation (8), regardless of the SOC when the vehicle arrives at the station by using different strategies, user's response to charging service fees is the response to the service fee difference among charging stations. The higher the difference, the more likely that the user will abandon shorter time strategy to pursue more advantageous strategy in terms of price.

For users who are in different locations, have different vehicle status and unit time value, their responses to the adjustment of charging service fee may not be the same. Therefore, it is necessary to carry out personalized analysis. To be more specific, the coordinated guidance strategy based on the adjustment of charging service fee needs to be formulated in combination with specific fast charging demand distributions.

2. Pricing Strategy of Charging Service Fee Based on Grid Benefit and Customer Satisfaction

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2.1 The Adjustment of Charging Power Based on the Acceptable Node Voltage of FCS

Considering the voltage variation characteristics of the distribution system, the PV curve can be drawn by using the continuous power flow method [15] to obtain the load power limit P_m. However, the power limit is often used to analyze the system's voltage stability margin, and the system's normal operation point is very far from the critical point of PV curve, thus, the power limit P_m cannot reflect the possible load access in the FCS. On the other hand, the normal operation of the distribution system needs to meets the constraints of power quality, and the load power corresponding to voltage amplitude limit (power quality constraint) can be obtained by PV curve, which is more stringent compared to the power limit P_m and is more likely to reflect the actual access of loads in the FCS. Therefore, the upper limit power P_{ssm} constrained by the power quality of distribution system can be defined as the node tolerability D of the node where the FCS locates:

$$D = P_{ssm} , \tag{9}$$

the tolerability D reflects the ability of FCS's receiving the fast charging loads.

Since charging piles are fixed, to take advantage of charging facilities and avoid EV users' waiting for too long, users' needs should be satisfied as much as possible. If the node voltage tolerability in distribution system during certain period is low, then the charging piles cannot provide full power charging for the EV users, but rather be reduced to avoid the bad effect on the distribution network.

According to the principle of equal distribution of the charging power, the charging power of each fast charging pile is shown in equation (10):

$$P_i = \min\{\frac{D}{n}, P_{\max}\} , \tag{10}$$

where n is the number of fast piles that are being charged; $P_{\max}$ is the maximum fast charge power that can be provided by fast filling piles.

2.2 Analysis of Grid Benefit and Customer Satisfaction Under Coordinated Fast Charging

In this paper, the goal of coordinated fast charging is to equilibrize the charging loads in the region. Hence, the equilibrium degree of FCSs is used to evaluate the coordinated fast charging effectiveness.

The charging capacity A of the FCS is defined as:

$$A = \min\{D, nP_{\max}\} . \tag{11}$$

It can be seen that the charging capacity of the FCS A is different from the voltage tolerability D of the power distribution system at the node where the FCS is located. After the completion of the FCS, the maximum access power of the fast charging loads is a rigid limit. The charging capacity A of the FCS means the maximum access power of fast charging loads considering this rigid limit.

On this basis, the occupancy U of the FCS is defined as:

$$U = \frac{\sum_{i=1,2,\cdots,m} C_{capi}(1 - SOC_i)}{A} . \tag{12}$$

In equation (12), $\sum_{i=1,2,\cdots,m} C_{capi}(1 - SOC_i)$ indicates the sum of the charging demands of m vehicles needed to be charged in the target period, and A is the charging capacity of FCS. The occupancy U reflects the charging density of FCS in the target period, indirectly reflecting the pressure of charging at this station. That is to say, the higher the occupancy U, the more the charging users and the higher the occupancy of charging piles, and the FCS is more likely to encounter queuing situation.

On the basis of occupancy U, the charging balance degree E of each FCS is defined as (13):

$$E = \min(U_1, U_2, \cdots, U_L) / \max(U_1, U_2, \cdots, U_L) , \tag{13}$$

where L is the number of fast-charge stations within the target area; U_i represents the occupancy of i-th fast-charge station.

The charging balance degree E represents the difference of the access pressure at each FCS concerning the charging loads. The smaller the value of E, the more unbalanced the distribution of charging loads, and those stations with higher occupancy U are more likely to be confronted with higher queuing risk, which is detrimental for both users and traffic. On the other hand, the greater the value of E, the more balanced the distribution of the charging loads, and the FCSs could satisfy the charging demands of the users and utilize the charging resources more effectively.

The charging balance degree E can reflect the positive benefit obtained by the power grid at different degrees of the coordinated fast charging. Therefore, this paper adopts this index to quantify and analyze the positive effect of the coordinated fast charging.

From the perspective of users, the satisfaction degree is directly related to the users' charging cost and charging time. In this paper, the overall charging satisfaction degree is measured by the relative values of user's charging cost and the overall charging time. The calculation formulas are separately:

$$C_i^* = \sum_{i=1}^{m} C_i \,/\, \sum_{i=1}^{m} C_{i0} \,, \tag{14}$$

$$T_i^* = \sum_{i=1}^{m} T_i \,/\, \sum_{i=1}^{m} T_{i0} \,, \tag{15}$$

where C_i^*, T_i^* is relative value of overall charge cost and overall charging time respectively; C_{i0}, C_i, T_{i0}, T_i is the total cost of charging and the total charging time of user i before and after charging service fee adjustment; m is the total number of fast charging EV users.

The guidance effect of coordinated fast charging based on the adjustment of charging service fees can be evaluated by the above charging balance degree E, the user's overall charging cost C_t and the user's overall charging time L_t. Theoretically, the optimal scheme should maximize the charge balance degree E, minimize the relative value of user's overall charging time T_i^*, and the relative value of user's overall charging cost C_i^* should be reduced due to the reimbursement of FCSs. Taking into account the profitability and the enthusiasm of the user response, the benefits obtained from charging balance degree are quantified and parts of the benefits are returned to the users proportionally. The benefits mainly come from the reduced network loss, power expansion cost and reactive power compensation costs.

Obviously, to increase the charge balance degree E, more users have to change their original charging locations, so it is necessary to set larger range of charging service fee within the scope permitted by the policy to attract users to abandon the shorter time scheme but charge in the FCS with lowest fee. This process will in turn lead to the increase of user's overall charging time T_t, thus, the relative value of user's overall charging time T_i^* increases.

It can be seen that the charging service fee is set as a multi-objective decision-making process when adjusting the charging service fee to coordinate fast charging demands. There exist conflicts among different targets, so the decision-maker needs to coordinate several indices to make comprehensive decisions when setting charging service fees.

2.3 The charging service fee pricing mechanism considering the equilibrium of FCS loads access and user satisfaction

From the analysis of Section 1.3, the selection of charging location for the price-sensitive users are largely dependent on the difference of charging service fee among FCSs. Therefore, the pricing mechanism of charging service fee can be divided into two steps: 1) coordinating the two objectives, namely the one that maximizes the charging balance degree E and the one minimizes the relative value of overall charging time T_t^*, and determining the difference of service fees among various FCSs; 2) determining the service fees at each FCS based on the principle that the relative value of

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overall charging cost C_i^* will be slightly reduced due to the reimbursement from the grid. The flow chart is shown as Figure 1:

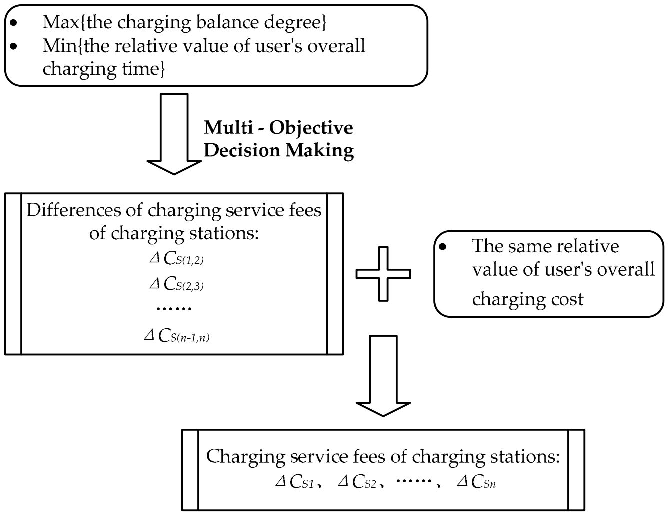

Figure 1. Flow chart of strategy devised for EV charging fees.

For the multi-objective decision-making problem involved in the first step, it can be described as followings:

$$\max E = \frac{\min(U_1, U_2, \cdots, U_n)}{\max(U_1, U_2, \cdots, U_n)} \tag{16}$$

$$\min T_i^* = \sum_{i=1}^{m} T_i \Big/ \sum_{i=1}^{m} T_{i0} \tag{17}$$

$$s.t. \begin{cases} T_i = f_i(x) & i = 1, 2, \cdots, m \\ U_j = g_j(x) & j = 1, 2, \cdots, n \end{cases}, \tag{18}$$

where x is the decision variable, namely the difference of service fee among FCSs, $x = \left[\Delta C_{s(1,2)}, \Delta C_{s(2,3)}, \cdots, \Delta C_{s(n-1,n)}\right]$; $f_i(x)$ is the function of the corresponding overall charging time for the i-th user's selecting the best charging scheme when the service fee difference is x. This function is related to user's charging location selection criteria, which is an abstract function that is very difficult to be solved. $g_j(x)$ is the occupancy function of the j-th FCS when the service fee difference is x, which is also an abstract function.

In this paper, the fuzzy programming method [16] is adopted to solve the multi-objective optimization problem, and the joint optimization target (16) and (17) are divided into two single-objective programming models to solve the corresponding Pareto optimal solution separately.

The objective function value of single-objective (16) optimal solution is E_{max}, and corresponds to $T_t^* = T_t^{**}$, the objective function value of single-objective (17) optimal solution is $T_t^*{}_{min}$, and corresponds to $E = E^*$. According to the Pareto optimal solution, it can be obtained that $T_t^{**} \geq T_t^*{}_{min}$, and $E^* \leq E_{max}$.

Consequently, the range of charging balance degree and users overall charging time is respectively [E^*, E_{max}] and [$T_t^*{}_{min}$, T_t^{**}]. The stretch index of the charging balance degree is defined as $E_{max} - E^*$, and the stretch index of user's overall charging time is defined as $T_i^{**} - T_t^*{}_{min}$, then a single objective programming model is established as follows:

$$\max g = \lambda$$

$$s.t.\begin{cases}\dfrac{\min(U_1,U_2,\cdots,U_n)}{\max(U_1,U_2,\cdots,U_n)}-\left(E_{\max}-E^*\right)\lambda\geq E^*\\ \sum_{i=1}^{m}T_i\Big/\sum_{i=1}^{m}T_{i0}+(T_t^{**}-T_{t\min}^{*})\lambda\geq E^*\\ T_i=f_i(x)\quad i=1,2,\cdots,m\\ U_j=g_j(x)\quad j=1,2,\cdots,n\end{cases}, \tag{19}$$

The solution obtained by fuzzy programming is a perfect solution of the multi-objective programming model.

For above-mentioned single-objective programming problem, which contains multiple abstract functions, it is difficult to solve with the analytical method. Therefore, a genetic algorithm is adopted to solve the above programming problem, whose solution steps are shown in Figure 2.

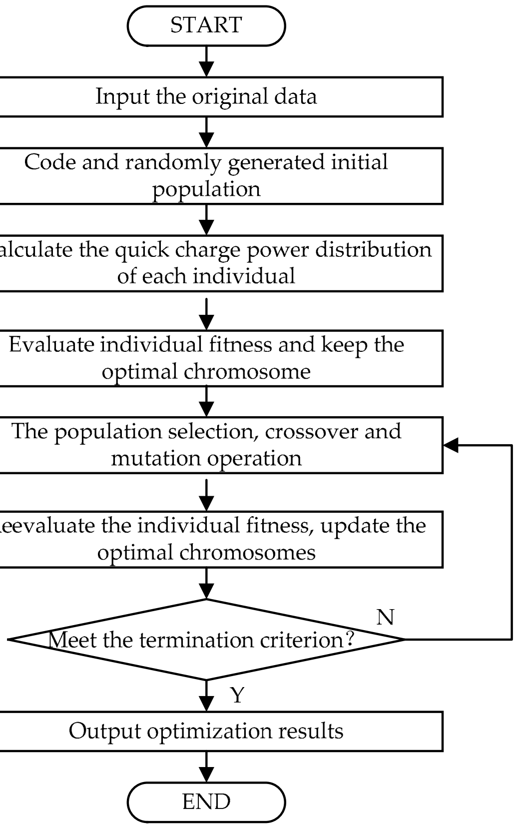

Figure 2. Flow chart of genetic algorithm for solving the single-target programming problem.

Combining the genetic algorithm and the fuzzy programming method, the satisfactory solution of the service fee differences can be obtained by fuzzy programming.

According to user's overall charging cost, the calculation of the service fees of charging stations can be completed then. The corresponding single-objective optimization model is shown as follows:

$$\min\left|\sum_{i=1}^{m}\left[C_i-(C_{i0}-C_R)\right]\right|$$

$$s.t.\begin{cases}C_i=h_i(x)\\ x(j)-x(k)=\Delta x_{j,j+1}+\Delta x_{j+1,j+2}+\cdots+\Delta x_{k-1,k}\\ i=1,2,\cdots,m;\ j=1,2,\cdots,n;\\ j<k;\end{cases}, \tag{20}$$

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where x is the decision variable, that is the service fee at each FCS, $x=\left[C_{s(1)},C_{s(2)},\cdots,C_{s(n)}\right]$. C_i is the overall charging cost within the target area after the adjustment of charging service fee; C_{i0} is the overall charging cost within the target area before the adjustment of charging service fee; C_R is the reimbursement for the system. $x(j)$ is the charging service fee for the j-th FCS, that is $x(j)=C_{s(j)}$; $\Delta x_{j,j+1}$ is the difference of charging service fee between *j*-th and *j+1*-th FCSs, which has been calculated in the previous steps; $h_i(x)$ is the function of overall charging cost for the *i*-th user when the charging service fee in each station is *x*, which is an abstract function.

The problem can also be solved by using the genetic algorithm. Eventually, the charging service fee at each FCS can be obtained.

3 Example Simulation

3.1 Simulation Idea and Data Sources Explaination

Based on the distribution of fast charging demands in the target region, combining with different types of user charging selection criteria, this paper employs fuzzy programming algorithm to achieve the multi-objective optimization of charging balance degree and user satisfaction degree, and then the charging service fee at each FCS is calculated and the changes of the indexes before and after cost adjustment can be obtained.

Before the popularization of EVs and ITS, the geographical locations and battery states of EVs in the road network cannot be recorded and accessed in real-time. In order to obtain the distribution of fast charging demands in the target region, this paper randomly generates the geographical locations and battery states of EVs in the road network (see in Appendix A), according to the geographical locations and remaining fuel state of the fuel vehicles in one evening peak in a specific road network system. Actually, in the future, with a myriad of EVs' access to ITS system, the geographical locations and battery states of EVs in the road network can be acquired in real-time.

Through the statistical analysis of the behavior characteristics of EV users, we can compile the statistical summary table shown in Table 1 in section 1.2, and adopts the disaggregate MNL model to obtain the probability of users adopting various charging location selection criteria. Yet the current number of EVs is limited, despite of a wide range of data collection based on Table 1. Thus, the statistical results still cannot characterize the future large-scale EVs' access scenario. Considering that the selection of the charging locations for EV users is similar to the selection of the charging location for the fuel vehicles, the statistical data in this paper for each factor (shown in Table 1) is obtained by adopting MNL model on the basis of the travel characteristics of the fuel vehicles in the existing road network. As a result, the ratio of users type Ⅰ, Ⅱ and Ⅲ in the target region is about 2:3:5.

In summary, due to the lack of relevant data, in the following simulation example, the given basic data such as the geographical locations and battery states of EVs in the road network, and the probability of different EV users adopting various types of charging location selection criteria are formed according to the existing traffic network and fuel vehicle distribution. However, the goal of this attempt is only to test and verify the methods and the effectiveness of the charging load scheduling strategy mentioned in this paper. Theoretically, whether the relevant data and the future scenario are mutually fitted will only affect the final assessment of the size of the specific indexes, but this will not change the equilibrium trend of charging loads before and after the adjustment of the charging service fee.

3.2 Parameters Setting and Simulation Calculation

The region shown in Figure 3 is used as the analysis object, the figure shows the main road traffic network in the target region, the two FCSs are located in point A and B, the pull-in direction is shown in Figure 3, where the distance between station A and intersection 11 is 220 meters and the distance between station B and intersection 25 is 380 meters. All roads are two-way lane, vehicles can only turn around at the intersections. The FCS A is located at node 23 of the IEEE 33 node distribution

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system shown in Fig. 4, and the FCS B is located at node 7 of distribution system shown in Fig. 4, the number of fast charging piles in these two stations is 20 and 30 respectively, and the maximum charging power is 80kW and the power factor is 98%. The unit price is 0.87 CNY / kWh, and before the charging service fee based coordinated fast charging strategy being implemented, the charging fee in these two stations is 1 CNY / kWh. Taking the targeted time period 20:00 - 22:00 as an example, there are 80 fast charging demands, whose spatial distribution is shown in Fig. 3 (the fast charging demands are related to the traffic flow, the higher the traffic flow, the more the distribution of charging demands). The geographical locations and battery states of EVs to be charged in the simulation region are shown in Table A1 in the Appendix A.

Figure 3. Sketch map of the transportation network in object region.

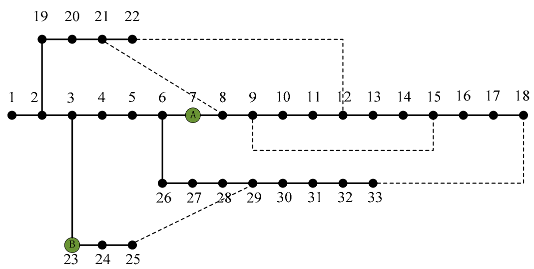

Figure 4. Structure of IEEE-33 distribution system.

The unit time value of users can be calculated by the per capita income in the targeted region according to the formula (7), and it is set to 20 CNY / hour in this case.

As the charging location selection results vary with different types of users, considering the user choice probability, for a single user, the expected values of the total charging time and the total charging cost are:

$$\overline{T} = p_I T_I + p_{II} T_{II} + p_{III} T_{III} , \tag{21}$$

$$\overline{C} = p_I C_I + p_{II} C_{II} + p_{III} C_{III} , \tag{22}$$

where $\overline{T}$ is the expected value of total charging time for the user, $\overline{C}$ is the expected value of the total charging cost for the user. p_I, p_{II}, p_{III} are the probability for class Ⅰ, class Ⅱ and class Ⅲ type users, respectively. T_I, T_{II}, T_{III} are the total charging time for class Ⅰ, class Ⅱ and class Ⅲ type users, respectively. C_I, C_{II}, C_{III} are the total charging cost in optimal charging location for class Ⅰ, class Ⅱ and class Ⅲ type users, respectively.

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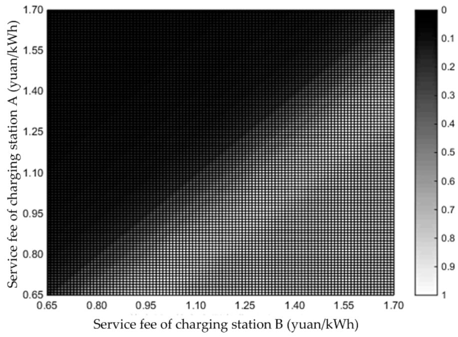
For FCSs, the expected value of total charging volume in the target period is:

$$\overline{Ep_i} = \sum_{j=1}^{m}\sum_{k=I}^{III} p_k I_{j,k,i} C_{capj}(1 - SOC_{j,i}) , \tag{23}$$

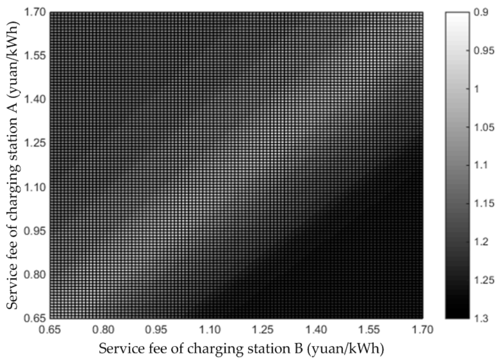
where, $\overline{Ep_i}$ is the expected value for total charging volume at charging station i; p_k is the probability of k-th (k= Ⅰ, Ⅱ and Ⅲ) type of users; $I_{j,k,i}$ is the charging location selection coefficient, whose value is set as 1 when the j-th (j=1,…,m) user is the k-th type of users, and its optimal charging location is charging station i, otherwise is set as 0; C_{capj} is the battery capacity for the j-th user; $SOC_{j,i}$ is the remaining SOC when the j-th user arrives at charging station i.

When the charging service fee is not adjusted, combined with the above-mentioned user response mode, the expected value of the charging balance degree $\overline{E_0}$ can be calculated according to formula (11)~(15), (21)~(23), thus $\overline{E_0} = 0.2811$.

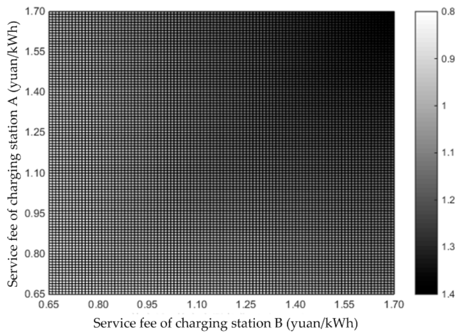
Similarly, the expected value of charging balance degree and the relative expected values of overall charging time and overall charging cost of station A and B under different charging service fees can be calculated, the results are shown in Figure 5.



(a) Expected value of charging balance in different charging service fees



(b) Expected value of total charging time in different charging service fees



(c) Expected value of total charging cost in different charging service fees

Figure 5. Guiding effects of different charging service fees.

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It can be seen from Figure 5 (a) and (b) that the dividing line between the charge balance and the users' overall charging time is basically parallel to the diagonal, which further explains that the charging balance degree and the relative value of user's overall charging time are determined by the difference of charging service fees between two charging stations.

It can also be concluded from Figure 5 (c) that the relative value of users' overall charging cost is radially distributed, the higher the charging service fee of these two FCSs, the more expensive the users' overall charging cost, and vice versa.

The acceptable range of the charge balance degree is $E \geq 0.8$; and the acceptable range of the relative value of users' overall charging time is $T_t^* \leq 1.15$; Due to EV users' response toward the charging cost, the charging balance degree in the target region increases, the voltage of each node in the distribution system more balanced, the network loss reduced, and the additional capacity and reactive power compensation at fast charging nodes become smaller, thus the economic benefit of the power grid is improved (this paper and does the initial accounting aimed mainly at the reactive power equipment investment operating costs). But the EV users' overall charging time increases. To ensure the user benefits, grid companies or FCSs should reimburse part of the benefits to users to reduce their overall charging cost. The amount of reimbursement will directly affect the user dependency, but it will not be analyzed in detail here due to space limitation.

This paper only assumes that the amount of reimbursement of the grid is 2% of the total charging cost, and the relative value of users' overall charging cost is maintained as $C_t^* \approx 0.98$ (0.978~0.982), Based on Figure 5, the feasible range of charging service fee of these two FCSs is shown in Figure 6.

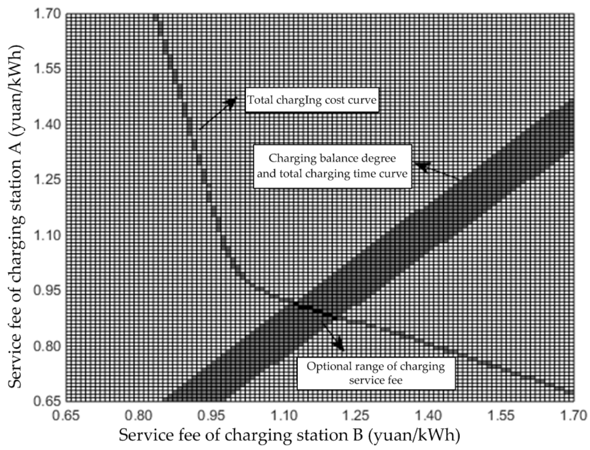

Figure 6. Feasible domain of charging service fees.

Using the genetic algorithm and fuzzy programming method, the satisfactory solutions of charging service fee for station A and B are 0.89 CNY/kWh and 1.17 CNY/kWh, respectively. In this scenario, the grid benefit (the relative charging balance degree of FCSs in the target region $\overline{E}'$) and user satisfaction degree (the relative values of users' overall charging time $\overline{T_t^*}'$ and charging cost $\overline{C_t^*}'$) are separately:

$$\overline{E}' = 0.9211, \quad \overline{T_t^*}' = 1.1297, \quad \overline{C_t^*}' = 0.981$$

Hence, the grid balance degree increases from 0. 2811 to 0.9211 after the adjustment of charging service fee, the distribution of charging loads becomes more uniform, and the charging infrastructures are fully utilized. Yet, the users' overall charging time has slightly increased by 12.97%; but the users' overall charging time has reduced by 1.9%, considering various types of users, a large proportion of users are price-sensitive, they are willing to pay a certain amount of time cost to obtain the charging benefits. Therefore, users are more likely to accept such coordinated fast

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charging strategy. and the node voltage over-limit and voltage offset volume in the IEEE 33 system at this moment is shown in Table 2.

Table 2. Voltage off-limit situation in IEEE-33 system.

Scenes	**The over-limit voltage node**	**The most serious voltage offset value (per unit value)**
Random access of charging load	9、10、11、12、13、14、15、16、17、18、28、29、30、31、32、33	0.919573
Change the charging fees to regulate EVs	13、14、15、16、17、18、30、31、32、33	0.921568

According to the requirement of GB/T12325-2008 "Power quality and power supply voltage offset", the limitation of power supply voltage offset should be "20 kV and below three phase power supply voltage offset should be ±7% of nominal voltage" (China national standardization management committee, 2008).

It can be seen from Table 2 that after the adjustment of charging service fee, the range of off-limit voltage node is reduced, the voltage offset is also reduced, and thus less reactive power compensation equipment are required. However, due to the large access of charging loads to the grid, these two scenarios both encounter the problems of off-limit voltage and reactive power deficiency when the grid is operating in peak-load period, and additional reactive power compensation devices are required.

Static Var Generator (SVG) is the third generation reactive power compensation device after SVC [17]. It has the advantages of long life span, high stability, fast response and low harmonic content. This paper assumes that the reactive power deficiency is provided by SVG, whose cost accounting method is shown in Table A2 in the Appendix A. The reactive power compensation investment costs after the adjustment of charging service fee is shown in Table 3 after calculation.

Table 3. Cost of reactive-load compensation equipment before and after charging fee adjustment.

Scenes	**Configuration capacity of reactive power compensation device（MVar）**	**Initial investment cost（ten thousand CNY）**	**Annual operating costs（ten thousand CNY）**	**The most serious voltage offset value after reactive compensation (per unit value)**
Random access of charging load	9.6	324	23.6	0.9373
Change the charging fees to regulate EVs	7	220	18	0.9427

As can be seen from Table 3, for the 10kV distribution system given in the simulationcase, through the adjustment of charging service fee, the cost of initial reactive power equipment can be effectively reduced by 1.04 million CNY, and the annual operating cost is reduced by 56,000 CNY.

Take into consideration that the penetration of EVs is relatively small nowadays, there are only two FCSs being designed in the distribution network of the simulation system, and only 80 fast charging demands are generated during the peak-load period. With the rapid development of EVs, the number of FCSs and fast charging demands will increase continually, and considerable economic and social benefits will be brought by the employ of charging service fee to orderly guide the charging behaviors.

4. Conclusions

This paper has proposed a price-setting strategy concerning the charging service fee at FCSs considering both the charging balance degree and user satisfaction degree in the target region. This method first adjusts the charging service fee to guide the fast charging behaviors of EVs in spatial dimension, and balance the fast charging loads at each charging station while ensuring user satisfaction degree. Taking the IEEE 33 nodes distribution network and the corresponding road

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network system as an example, based on the fast charging demand distribution in the target region, the price-setting of charging service fee at each FCS and the orderly guidance of fast charging loads are achieved. Finally, the simulation results show that the adjustment of charging service fee can effectively dispatch the distribution of fast loads in the spatial level, improve the local charging balance degree, and can be implemented easily due to its good user satisfaction degree.

It should be noted that currently, the safety and reliability evaluation system of EV-included distribution network is not mature, and the impact of fast charging loads' large-scale random access to distribution networks (including power quality, power flow distribution, voltage offset, overloading) remains to be further studied. On the other hand, the access of charging loads will cause the increase of backup power, transformer capacity and reactive power compensation equipment investment. Thus, the economic costs need to be further analyzed. This paper only considers the charging balance degree as the evaluation index of the distribution network, which has certain limitations. In conclusion, the determination of the reimbursement scale of the system after the equilibrium of the charging loads still needs to be refined and such problems are definitely the focus of future research.

Acknowledgments: Project supported by National Natural Science Foundation of China (51537003).

Author Contributions: All the participants have contributed a lot to the formation of this paper. Shu Su has come up with the essential idea for this paper, and Hang Zhao went a step further to adding specific details to this idea, such as employing the M/M/C queuing theory and fuzzy programming method into this model. Hongzhi Zhang carried out the simulation in MATLAB and verified the correctness of this method, Xiangning Lin gave guidance and provided technical assistance during the course.

Conflicts of Interest: The authors declare no conflict of interest. And the founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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Appendix A

Table A1. Location and battery capacity of fast charging users in the target area.

EV Num.	EV Location			Battery Parameter		EV Num.	EV Location			Battery Parameter	
	The previous intersection numbers	The next intersection numbers	Distance from the next intersection /km	Battery capacity /kWh	SOC		The previous intersection numbers	The next intersection numbers	Distance from the next intersection /km	Battery capacity /kWh	SOC
1	2	3	0.91	18	0.39	41	18	19	0.12	42	0.34
2	5	4	0.73	33	0.50	42	20	19	0.82	33	0.33
3	1	6	0.96	12	0.17	43	19	20	0.24	15	0.38
4	3	8	0.52	26	0.42	44	19	20	0.63	18	0.38
5	3	8	1.05	38	0.38	45	19	20	0.78	38	0.28
6	9	4	0.98	26	0.25	46	21	20	0.44	15	0.35
7	7	11	1.20	15	0.32	47	21	20	0.87	15	0.34
8	8	12	0.64	18	0.38	48	21	20	0.93	12	0.40
9	12	8	0.53	12	0.64	49	20	21	0.74	26	0.44
10	12	8	0.74	18	0.57	50	22	16	0.78	42	0.44
11	9	13	0.48	26	0.24	51	23	17	0.43	15	0.28
12	9	13	1.31	12	0.59	52	23	17	0.54	33	0.36
13	10	11	1.27	90	0.41	53	18	24	0.27	70	0.25
14	10	11	0.93	26	0.34	54	18	24	0.82	26	0.26
15	11	12	0.69	42	0.41	55	24	18	0.85	15	0.35
16	13	12	0.65	15	0.33	56	19	25	0.83	18	0.47
17	12	13	0.38	15	0.34	57	25	19	0.85	42	0.29
18	14	13	0.81	33	0.47	58	25	19	0.93	38	0.38
19	13	14	0.22	18	0.46	59	20	26	0.22	15	0.33
20	13	14	0.75	15	0.46	60	20	26	0.89	26	0.44
21	15	14	0.64	42	0.40	61	26	20	0.73	12	0.26
22	10	16	0.38	18	0.25	62	26	20	0.64	15	0.35
23	11	17	0.62	15	0.41	63	21	27	0.42	26	0.39
24	17	11	0.88	33	0.48	64	22	23	1.15	26	0.44

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EV Num.	EV Location			Battery Parameter		EV Num.	EV Location			Battery Parameter	
	The previous intersection numbers	The next intersection numbers	Distance from the next intersection /km	Battery capacity /kWh	SOC		The previous intersection numbers	The next intersection numbers	Distance from the next intersection /km	Battery capacity /kWh	SOC
25	18	12	0.80	26	0.39	65	23	24	1.09	15	0.47
26	13	19	0.37	12	0.43	66	25	24	0.68	42	0.36
27	13	19	0.49	26	0.41	67	24	25	0.43	15	0.23
28	13	19	0.92	18	0.33	68	26	25	0.47	15	0.29
29	19	13	0.17	12	0.37	69	26	25	0.58	33	0.27
30	19	13	0.86	18	0.29	70	25	26	0.30	26	0.54
31	14	20	0.53	15	0.42	71	27	26	0.27	12	0.30
32	20	14	0.52	15	0.26	72	27	26	0.73	18	0.41
33	20	14	0.61	38	0.26	73	26	27	0.48	38	0.33
34	15	21	0.85	15	0.29	74	30	23	1.01	26	0.42
35	21	15	0.44	12	0.11	75	31	24	0.77	33	0.29
36	17	16	1.38	15	0.47	76	25	32	0.35	38	0.24
37	18	17	0.79	33	0.38	77	32	25	0.83	15	0.24
38	17	18	0.81	70	0.29	78	33	27	0.97	18	0.39
39	19	18	0.23	26	0.46	79	30	31	1.66	26	0.34
40	19	18	0.39	26	0.21	80	33	32	0.13	18	0.33

Table A2. Cost accounting table of investment and maintenance for SVG in distribution network.

Distribution Voltage Level (kV)	SVG Capacity (MVar)	Rated Service Life (year)	Investment Costs (ten thousand CNY)	Annual Operation Cost (ten thousand CNY)	Industry Discount Rate(%)
3.8	0.3	18	7	0.8	15
3.8	1	18	50	2	15
10	2	18	70	5	15

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Appendix B *Dynamic Charging service Model of EV based on M/M/s Queuing Theory*

Through the sample study of the service objects and the arrival time, the statistical law of the quantity index (like waiting time, queue length, service intensity, etc.) of the system is available and can be used to reconstruct the process of service delivery and ensure the agency's cost or some other indicators, thus achieving multi-objective optimization. EVs' charging service behaviors are mutually independent, which meet the characteristics of stationarity, non-aftereffect property and generality. The M/M/c queuing theory is adopted in this paper to analyze the charging process of EVs and to estimate the cars' arrival probability along with occupancy rate of charging equipment. The assumptions made in this paper are listed as follows:

- The arrival pattern of the cars waiting to be charged is subject to Poisson's flow distribution $z(y_i,t)$;
- EV's charging completion rate $\mu_0(t)$ of each vehicle is independent and follows negative exponential distribution;
- Each charging station is configured with s charging piles;
- The queuing EVs follow the First-come First-served rule

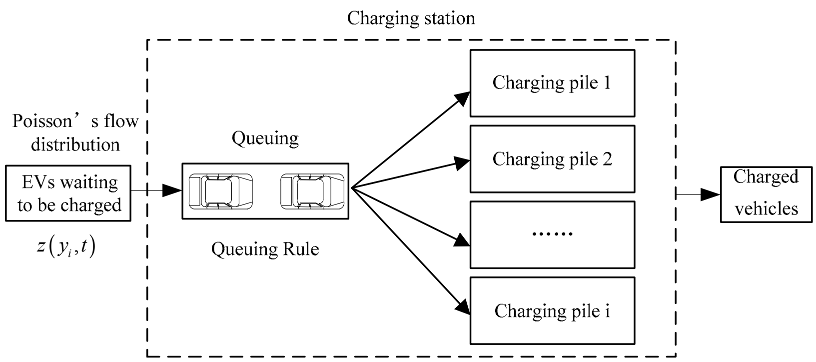

Figure B1. Queuing model of charging station based on the M/M/s model

The formula of calculation, which is defined as the occupancy rate of charger, ρ is given as below under the corresponding assumptions:

$$\rho = \frac{z(y_i,t)}{s\mu_0(t)}$$

According to the M/M/s queuing theory and the state transition relation of charging station, the probability distribution of EV charging service can be described as follows:

$$Q_n(t) = \begin{cases} \dfrac{1}{n!}\left(\dfrac{z(y_i,t)}{\mu_0(t)}\right)^n Q_0 & if \quad 0 \le n \le s-1 \\ \dfrac{1}{s!s^{n-s}}\left(\dfrac{z(y_i,t)}{\mu_0(t)}\right)^n Q_0 & if \quad n \ge s \end{cases}$$

$$Q_0 = \left[\sum_{n=0}^{s-1}\frac{1}{n!}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^n + \frac{1}{s!}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^s\left(\frac{s\mu_0(t)}{s\mu_0(t)-z(y_i,t)}\right)\right]^{-1}$$

where $Q_n(t)$ is the probability of the steady state that the number of EVs waiting to be charged remains at the node n, and $\sum_{n=0}^{\infty} Q_n = 1$.

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The expected value of the occupancy rate of the charging piles and the charging load of the station can be mathematically formulated as follows:

$$B(t) = \sum_{n=0}^{\infty} \min(n,s) Q_n(t) = \frac{z(y_i,t)}{\mu_0(t)}$$

$$P_d(y_i,t) = p_{av} B(t) = p_{av} \frac{z(y_i,t)}{\mu_0(t)}$$

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