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Load Forecast of Electric Vehicle Charging Station Considering Multi-Source Information and User Decision Modification

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Abstract: In view of the current multi-source information scenario, this paper proposes a decision-making method for electric vehicle charging stations (EVCSs) based on prospect theory, which considers payment cost, time cost, and route factors, and is used for electric vehicle (EV) owners to make decisions when the vehicle's electricity is low. Combined with the multi-source information architecture composed of an information layer, algorithm layer, and model layer, the load of EVCSs in the region is forecast. In this paper, the Monte Carlo method is used to test the IEEE-30 model and the traffic network based on it, and the spatial and temporal distribution of charging load in the region is obtained, which verifies the effectiveness of the proposed method. The results show that EVCS load forecasting based on the prospect theory under the influence of multi-source information will have an impact on the space–time distribution of the EVCS load, which is more consistent with the decisions of EV owners in reality.

Keywords: load forecast; electric vehicle; prospect theory; multi-source information

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1. Introduction

At present, energy from fossil fuels is becoming scarce. With the development of renewable energy generation and electric vehicle (EV) power battery technology, all countries are vigorously promoting the popularity of EVs to promote the clean energy of transportation [1,2]. Unlike residential or industrial loads, which have strong periodicity, the high volatility of EV charging demands poses more challenges to the power grid [3]. Therefore, it is of great importance to predict EV load and formulate demand response plans [4].

The prediction of electric vehicle charging station (EVCS) scenarios are often based on existing historical data. Vehicle GPS data [5] and historical electricity price data [6] can be collected to make a decision after car owners' comparison. Reference [7] applied hierarchical methods after dimensionality reduction, and data were input into multiple benchmark prediction models. According to Reference [8], the behavior of car owners charging EVs cannot be controlled, so the ARIMA model is used to aggregate and forecast the demand for charging equipment in the road network. Gilanifar et al. analyzed the flexible load from multiple charging stations, learned a Gaussian process for each node, and updated the Gaussian process parameters through the square error of k-means clustering in the iteration [9]. In Reference [10], a long and short-term memory network is applied to predict vehicle travel behavior and cluster departure and arrival time to realize load forecast.

However, in the absence of historical load data, it is very important to analyze the user's behavior to predict the load in the region. Different probability distribution functions are used to match the vehicle's daily mileage, the probability distribution of charging [11], driving distance, and number of battery replacements per hour [12], which are highly subjective. Moon et al. [13] analyzed consumers' preferences for fast and slow charging, and [14] further divided users' charging habits into multiple behavioral clusters to analyze the flexibility of EV charging load.

Reference [15] matches the vehicle SOC monitored by the Internet of Things (IoT) with the status of EVCSs and makes charging choices for users. Charging scenarios are classified by References [16,17], and users' charging behaviors in different scenarios under different charging powers and driving modes are analyzed through maps. However, in the practical application of the above articles, some users may be worried about data privacy and unwilling to upload relevant information for analysis.

The stochastic framework based on unscented transform in Reference [18] models the uncertain variables of plug-in vehicles, such as charging strategy and the number of vehicles needing to be charged. Reference [19] proposes a method based on SOC combination, which dynamically distributes the charging power of EVCSs.

This paper proposes a load forecast model for EVCSs based on multi-source data and prospect theory. Firstly, the travel characteristics of private car and taxi owners are analyzed to construct a travel chain. Secondly, the velocity of different roads in the road network at different times is calculated in the traffic flow model. Then, when the car owner has charging demand, the prospect theory is used to analyze the influencing factors and modify the decision that has been made at a particular node in choosing a charging station. Finally, based on the decisions made by each car owner, the spatio-temporal distribution prediction of EVCS load is constructed.

The content of this paper is arranged as follows. Section 2 proposes the multi-source information interaction system and the load forecast model framework of EVCSs. Section 3 proposes the decision-making model of EV owners based on prospect theory. Section 4 conducts calculation example analysis and Section 5 concludes the paper.

2. Framework of EVCS Load Forecasting Model Based on Multi-Source Information and Prospect Theory

At present, with the development of the internet of vehicles technology [20], car owners can intuitively obtain various types of information through mobile phone apps before and during the journey, such as congestion of route, electricity price of EVCSs, and even the queuing situation. All this information will exert a great influence on the decision-making scenario of EV owners in choosing charging places, thus affecting the distribution of charging loads to a certain extent.

2.1. Establishment of Multi-Source Information Interaction System

The framework of the multi-source information interaction system proposed in this paper can be divided into three layers: multi-source information layer, algorithm layer, and model layer, respectively, as shown in Figure 1 below.

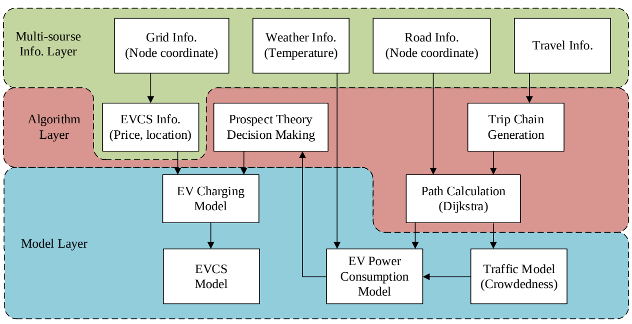

Figure 1. Framework of multi-source information interaction system.

In the multi-source information layer, travel information refers to the residence and departure times of cars. Information on EVCSs includes location and time-of-use (TOU) price. In the algorithm layer, the Dijkstra algorithm is used to calculate the shortest path. When the EV battery is low, the proposed EVCS decision algorithm is adopted to select the best charging station considering multiple factors. In the model layer, the velocity is obtained by the number of cars on each road. After combining EVCS information with the decision of EV owners, the EVCS model can be obtained, including the state of chargers, SOC of the vehicle, queuing, etc.

2.2. Framework of EVCS Load Forecasting Model

First, the travel chain of each vehicle is generated through travel information. There are three types of travel chains for private cars: "simple chain", "special chain" (round-trip trips to a special area after going to the original destination), and "complex chain", as shown in the following Figure 2.

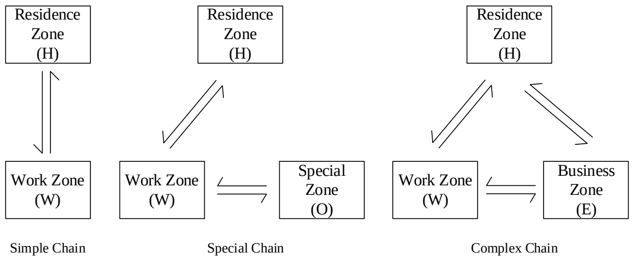

Figure 2. Travel chain of private cars.

Departure time follows a function based on Weibull distribution:

$$f(t) = \frac{k}{\varphi}\left(\frac{t-\gamma}{\varphi}\right)\exp\left[-\left(\frac{t-\gamma}{\varphi}\right)^k\right] \quad ,t \geq \gamma \tag{1}$$

where k is shape parameter. φ is scale parameter, and the unit is min. γ is a position parameter in minutes.

In this paper, the departure time of private cars follows Formula (1) with k = 1.5, γ = 360 and φ = 100. The parking time in working and commercial areas follows the normal distribution of N~(540,15) and N~(60,15), respectively, and parking time in special areas follows random distribution in [20,60].

The OD (Original-Destination) matrix method is used to generate the taxi travel chain; that is, taxis have a different probability of going to different destinations at different times of the day, as shown in Table 1. In this paper, destinations are roughly divided into "residential area", "business area", and "work area" to simplify the analysis, and the probabilities are roughly divided according to the commuting time.

Table 1. OD matrix at 22:00~7:00 (+1) on weekdays.

Departure \Destination	Residence	Work	Business
Residence	0.8	0.1	0.1
Work	0.8	0.1	0.1
Business	0.7	0.1	0.2

Taxi departure time follows Formula (1) with parameters k = 1.15, γ = 360, and φ = 30, and stay time in different regions varies at different times. OD matrix and stay time of taxis are shown in the Appendix A.

In the next step, the path and road network speed model can be generated. In the model of this paper, the generation of vehicle routes does not consider the influence of drivers' decision-making caused by congested road conditions, and the Dijkstra algorithm is used to calculate the shortest route. Given the starting time and path of journey, the modified Greenshields traffic flow model is used to obtain road speed:

$$Q = -av^2 + bv - c \tag{2}$$

where Q is the volume of traffic flow, v is road speed, and a, b, c are the parameters.

The vehicle energy consumption model consists of two factors: mileage and air conditioning state. The calculation interval in this paper is 1 minute. W_t represents energy consumption of the vehicle, which is calculated as follows:

$$W_t = W_{driving} + W_{AC} \tag{3}$$

where $W_{driving}$ is the power consumption of mileage.

As speed limits in urban areas are generally no higher than 60 km/h, in the case of known NEDC (New European Driving Cycle) and battery capacity, the driving energy consumption of the vehicle is deducted in the form of mileage. W_{AC} is the power consumption of air conditioning. Given the temperature curve, when the temperature is higher or lower than a certain value, it is regarded that cold air or heating is turned on. The energy consumption formulas are as follows:

$$W_{driving} = \frac{d}{NEDC} \cdot C_{battery} \tag{4}$$

$$W_{AC} = P_{AC} \cdot t \tag{5}$$

where d is the mileage of vehicles; $C_{battery}$ is the capacity of battery; P_{AC} is the power of air conditioner, 1.2 kW and 1.5 kW, respectively, when cold or warm air is turned on.

When the SOC of the vehicle is lower than a certain value (this paper takes 0.05), the EV owner will decide which charging station to charge based on the decision method proposed in this paper. Thus, the load value of each EVCS can be predicted.

3. EV Owner Decision Model Based on Prospect Theory

3.1. Prospect Theory Decision Model

In the model of this paper, the endurance of private cars will be enough to support daily commuting, so private car owners charge with slow chargers in residential areas. This decision model is mainly aimed at owners of commercial vehicles (i.e., taxis).

The prospect theory considers factors that influence decision-making, makes risk assessments by comparing with acceptable standards of consumers, calculates gain and loss, and then calculates weighted prospect value to select the EVCS with the best prospect. The process for EV owners is as follows:

First, the original decision matrix is defined in Formula (6):

$$X_{od} = \left(x_{t,ij}\right)_{m\times n} = \begin{bmatrix} x_{t,11} & \cdots & x_{t,1n} \\ \cdots & \cdots & \cdots \\ x_{t,m1} & \cdots & x_{t,mn} \end{bmatrix} \tag{6}$$

where $x_{t,ij}$ is the jth traffic characteristic value (TCV) of the vehicle going to the ith EVCS at time t.

TCV is various factors that the EV owner needs to consider and convert into profit or loss value. The calculation method of TCVs will be elaborated in Section 3.2.

The prospective values of various categories obtained from all EVCSs are arranged in the direction from beneficial to unbeneficial to the EV owner, called $x_{c1}, x_{c2}, \ldots, x_{c,TCV_{Valid}}$. The standard value of each TCV accepted by car owner (S) can be obtained by the following Formula (7):

$$S = \frac{0.5 \cdot \sum_{1}^{s_1} x_c + 0.3 \cdot \sum_{s_1+1}^{s_2} x_c + 0.2 \cdot \sum_{s_2+1}^{TCV_{Valid}} x_c}{0.5 \cdot s_1 + 0.3 \cdot (s_2 - s_1) + 0.2 \cdot (TCV_{Valid} - s_2)} \tag{7}$$

where TCV_{Valid} is the number of reachable charging stations, while some EVCSs may not be reachable due to insufficient endurance mileage.

To highlight the impact of decisions that are more beneficial, the TCV that is more favorable to the EV owner has a greater weight, so the corresponding value is given a weight of 0.5, 0.3, and 0.2. s_1, s_2 are the intervals of weights, respectively, which are calculated by the formulas below:

$$s_1 = \text{floor}(TCV_{Valid}/3) - 1 \tag{8}$$

$$s_2 = TCV_{Valid} - [\text{floor}(TCV_{Valid}/3) + 1] \tag{9}$$

Then, the prospect value function of car k choosing a charging station i in time period t is:

$$v_{tkij} = \begin{cases} \left(d_{kij}\right)^{\alpha}, d_{kij} \geq 0 \\ -\left(-d_{kij}\right)^{\beta}, d_{kij} < 0 \end{cases} \tag{10}$$

where α and β are, respectively, risk sensitivity coefficients, both of which are set at 0.88 in this paper [21], and d_{kij} is the difference between jth TCV of charging station i chosen by car k and the car owner's acceptable standard.

The analytic hierarchy process (AHP) is used to determine the proportion of each traffic characteristic. The importance relation between each two TCVs is compared in Table 2.

Table 2. Comparison of importance decided by AHP.

Array	Payment	Time Cost	Route
Payment	1	1/2	2
Time Cost	2	1	3
Route	1/2	1/3	1

Where 1,2,3 indicate one factor is equally, slightly, or significantly more important than the other, respectively. The reciprocal of each number means the opposite.

Acquired by calculation, the weights of payment cost, time cost, and route factor are 0.297, 0.540, and 0.163, respectively. The weight of TCV of item j is denoted as ω_{tj}.

The weight function of the owner's gain and loss can be obtained by calculation, namely $\pi_{tj}{}^{+}$ and $\pi_{tj}{}^{-}$:

$$\pi_{tj}^{+}(\omega_{tj}) = \frac{\omega_{tj}^{\gamma}}{\left[\omega_{tj}^{\gamma} + (1-\omega_{tj})^{\gamma}\right]^{1/\gamma}} \tag{11}$$

$$\pi_{tj}^{-}(\omega_{tj}) = \frac{\omega_{tj}^{\delta}}{\left[\omega_{tj}^{\delta} + (1-\omega_{tj})^{\delta}\right]^{1/\delta}} \tag{12}$$

where γ is coefficient of risk-return attitude, which is 0.61, and δ is risk-loss attitude coefficient, which is 0.69.

Then, the prospect value of car k choosing the ith charging station in time period t is:

$$v_{tki} = v_{tki}^{+} + v_{tki}^{-} = \sum_{j}^{m} v_{tkij}^{+} \cdot \pi_{tj}^{+} + \sum_{j}^{m} v_{tkij}^{-} \cdot \pi_{tj}^{-} \tag{13}$$

Once the prospect value is calculated, EV owners will choose EVCSs with the highest prospect value for charging.

However, with the changing traffic conditions, road congestion and EVCS conditions will change in real-time. In this model, EV owners will make adjustments according to the situation at every road node before arriving at the charging station after making a decision.

3.2. Determination of TCVs in Prospect Theory

When looking for social fast charging stations, EV owners will consider many factors, such as TOU price, power consumption needed to get to EVCSs, and the queuing of charging stations. The model in this paper classifies various factors into 3 TCVs, namely payment cost, time cost, and route factor.

The payment cost refers to the electricity charge paid by the car owner after calculating the expected queuing time, and the formula is as follows:

$$x_1 = \sum_{t=t_{EVCS}}^{t_{charging}} W_{charging}(t) E_{price}(t) \tag{14}$$

where $W_{charging}(t)$ is the amount of charge at the moment t, $E_{price}(t)$ is TOU electricity price at the moment, t_{ECVS} is the time when the vehicle starts charging after arriving at the charging station and passing the estimated queuing time, and $t_{charging}$ is the estimated charging time.

Time cost refers to the waiting time in EVCS calculated according to the SOC state of each charger and the queuing after browsing the status of EVCS. This time plus the time it takes to charge, is converted into gain corresponding to loss.

$$x_2 = \left(t_{queue} + t_{charging}\right) \cdot v_{ave} \cdot \varepsilon \tag{15}$$

where v_{ave} is the average traffic speed of all roads in the current road network. The paper does not consider the variable currency sensitivity coefficient [22]; that is, it believes that users have the same sensitivity when facing different sizes of gains and losses. Then ε is the estimated profit per kilometer, which is set at RMB 2.8 in this paper.

Route factor, namely, the average benefit of the vehicle to pick up orders in the nearby area after charging minus the loss of waiting time. If multiple regions are covered, the average value is taken. Route factor is calculated as follows:

$$x_3 = \frac{1}{num_{dest}} \sum_{1}^{num_{dest}} \left[\left(OD_{dest} \cdot d_{dest} - t_{wait} \cdot v_{ave} \right) \cdot \varepsilon \right] \tag{16}$$

where d_{dest} is the length to the destination, and OD_{dest} is the OD matrix probability to the corresponding destination.

4. Case Study and Discussion

4.1. Model Construction

The road network model adopted in this paper contains 50 blocks, 72 nodes, and 120 roads [23] covering an area of 625 km^2; there are 200,000 private cars and 2000 taxis. All roads are divided into two classes. For the high street, the values of a, b, c in Formula (2) are 5.4, 309.6, and 2761, respectively. For the collector streets, the three parameters are taken as 4.65, 260.9, and 2092.4, respectively.

There are 12 fast EVCSs on the road network, as shown in the green circle in Figure 3. According to different coverage areas, TOU prices of different levels are set, which are shown in the Appendix A. Each station contains 30 chargers with a power rating of 60 kW. The rated charging power of taxis is 50 kW.

The Greenshield model is applied to calculate speed in the road network, and the results are shown in Figure 4. As can be seen, road speed in the network presents a double valley shape caused by morning and evening rush hours.

4.2. Selection of Experiment Times and Accuracy Measure

In this paper, the Monte Carlo method is used to reduce the error of the results. The variance coefficient method [23] is taken as the evaluation standard, and the formula used is:

$$E = \max E_t = \max \left\{ \frac{\sigma_t(M_t)}{\sqrt{I} \cdot \bar{M}_t} \right\} \tag{17}$$

where σ is the calculation symbol of standard deviation, M_t is the load value at time t, $\bar{M}_t$ is the mean value of load at time t, and I is the number of Monte Carlo cycles.

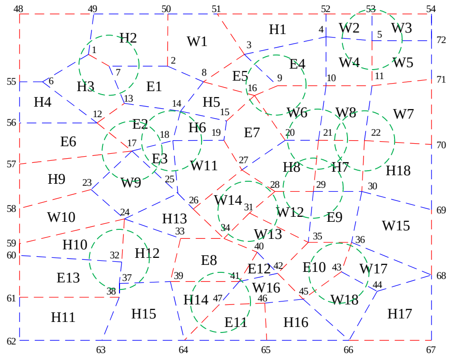

Figure 3. Road network model and EVCS location.

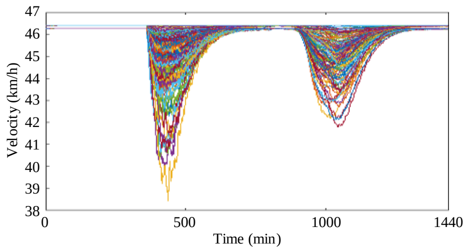

Figure 4. Road speed derived from Greenshield model.

$E \leq 0.1$ regards convergence of the point. The results are evaluated in the form of accuracy (i.e., number of convergence points divided by all variance non-zero value points).

Monte Carlo experiments results conducted 500~15,000 times can be seen in Figure 5. For EVCSs with poor results, 15,000 times of experiments can greatly improve the accuracy, while some with better results do not improve significantly. In order to balance calculation performance and prediction effect, the comparison object of this paper will take Monte Carlo cycles as 15,000. The average value of forecast accuracy with different cycles is shown in following Table 3.

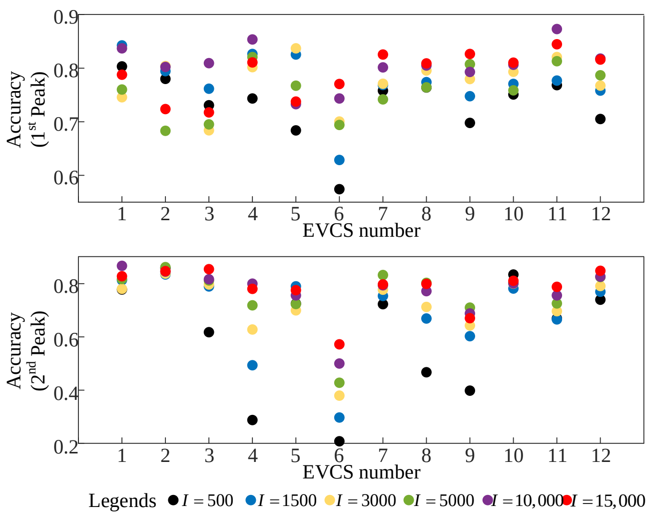

Figure 5. The relationship between the number of Monte Carlo cycles and forecast accuracy.

Table 3. Average prediction accuracy under different Monte Carlo cycles.

I in (17)	1st Peak Ave. Accuracy(%)	2nd Peak Ave. Accuracy(%)	Operation Time (min)
500	73.00	60.89	20
1500	77.30	68.85	58
3000	77.51	71.19	110
5000	75.77	75.51	189
10,000	80.63	76.85	376
15,000	**79.00**	**78.10**	**625**

4.3. Validity Analysis of Prospect Theory Decision Making

The comparison background of this section is a scenario where the penetration rate of electric taxis (ETPR) is 50% (i.e., 1000 of 2000 taxis are EVs in the region). Compared with the proposed real-time decision-making method of EV owners based on prospect theory, there are two methods for comparison: (1) selecting the nearest EVCS for charging (i.e., Method 1), and (2) making a decision only once when the vehicle is low in power (i.e., Method 2).

As can be seen from Figure 6, charging stations usher in the first concentrated charging after 12:00. It can be obtained from the OD matrix that most taxis gather towards work areas at this time. Therefore, charging stations with an obvious queuing phenomenon are located in work and central areas, i.e., EVCS 3, 2, and 7(at nodes 5, 9, and 34).

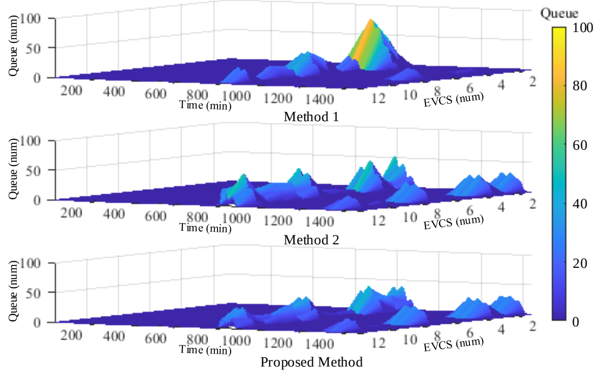

Figure 6. Comparison of queuing at EVCSs under different forecast methods.

In reality, queuing at charging stations for a long time inevitably affects drivers' income. After applying prospect theory to make decisions, the queues in some EVCSs are more evenly distributed. Furthermore, when EV owners make adjustments at each road node, the number of vehicles queued is reduced to 44, and the time for all EVCSs to end queuing is advanced from 15:53 to 15:03.

At the same time, some EVCSs with queuing vehicles in Method 1 have higher charging costs for drivers due to higher electricity prices, resulting in a reduction in the number of queuing vehicles (e.g., EVCS 4 at node 23) when using the proposed method.

From the point of view of the load curve shown in Figure 7, the load of each EVCS can be more evenly distributed, avoiding that some EVCSs are still at peak load for a long time while some of them have no vehicles in charge.

The comparison results of the three indicators of the load prediction method proposed in this paper are shown in Table 4. The three indicators are the first peak number of vehicles queuing, the time when vehicles end queuing at the first peak, and the time difference between EVCSs that enters the no-load state first and last.

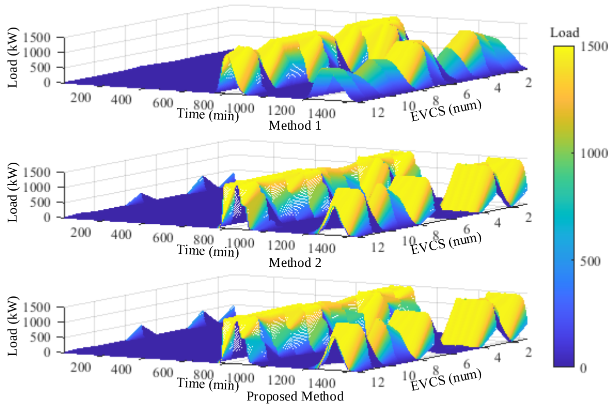

Figure 7. Load comparison of charging stations under different forecast methods.

Table 4. Peak number of queuing vehicles, finish queuing time, and idle time difference comparison.

Methods	1st Peak Queue Value	1st Queue Finish Time	Idle EVCS Time Difference
Method 1	84	16:05	135 min
Method 2	52	15:53	116 min
Proposed	44	15:03	42 min

Therefore, the decision-making method of EV owners proposed in this paper can guide EV owners to charge at relatively idle charging stations when queuing occurs at charging stations, thus avoiding long waiting times.

4.4. Spatial and Temporal Distribution Analysis of Charging Load under Different EV Penetration Rate

As shown in Figure 8 below, when the ETPR is 30%–50%, electricity price and distance to the charging station have a great influence on users' decisions, so some charging stations have queues while some do not.

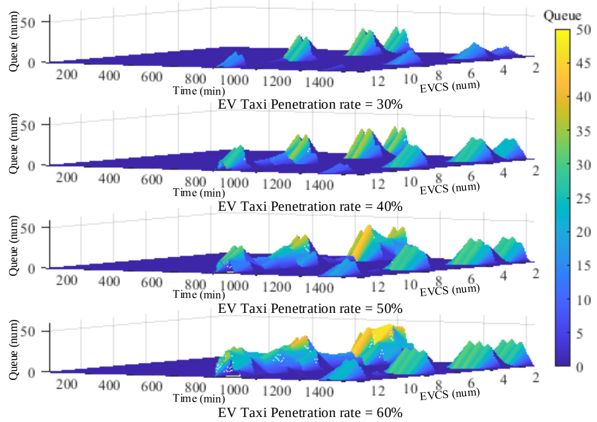

Figure 8. Longest queuing comparison under different ETPR.

When ETPR exceeds 50%, queuing occurs at all charging stations, so users need to make comprehensive consideration of multiple factors. Meanwhile, it can be seen that some charging stations that do not have a queue at 40% ETPR also have a short queuing at 50% ETPR.

Figure 9 below shows the peak load when the ETPR is 30%~60%. As can be seen from Figure 9, when the number of electric taxis rises, the increase of peak load is not a simple multiple growth due to the fixed number of chargers.

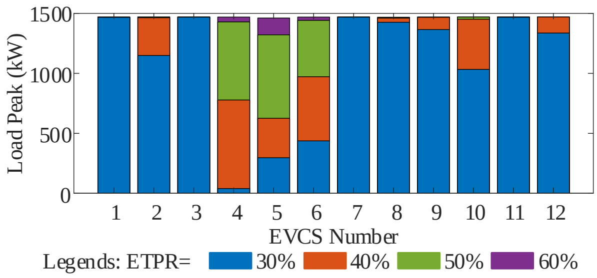

Figure 9. Comparison of peak load at the first charging peak under different ETPR.

Due to the gradual emergence of queuing, the decisions made by users in the face of queuing at peak charging hours make load dispersion more obvious. When ETPR increases from 40% to 50%, the peak charging loads of EVCS 4, 5, 6 with low values at noon increase from 50.6%, 29.7% and 38.4% of full load to 79.7%, 71.1%, and 77.9%, respectively.

The duration of each EVCS at 80% of full load at the first charging peak is shown in Figure 10. As the rated power of quick charging of taxis is 50 kW and that of quick chargers is 60 kW, the scenario analyzed in this figure is that the load of each EVCS reaches 80% of the full load.

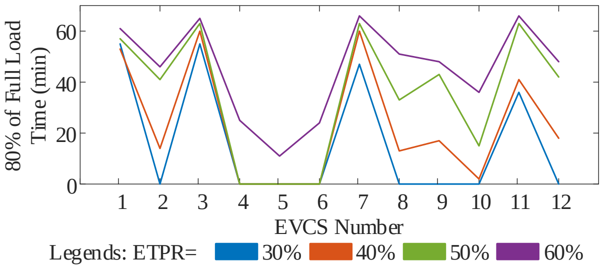

Figure 10. Duration of each EVCS at 80% of full load at the first charging peak under different ETPR.

When ETPR increases from 30% to 50%, the "full occupied time" of EVCSs that have reached 80% of full load (i.e., all chargers have cars charging) previously will increase significantly. However, when the ETPR increases from 50% to 60%, the "full occupied time" of these EVCSs change not much, while that of others will increase greatly.

As can be seen from Table 5, when the ETPR rises from 50% to 60%, the queuing ending time of EVCSs is delayed from 15:03 to 16:14, and the time difference between the first and last charging stations entering the zero-load state is also greatly extended. Therefore, it can be concluded that the number of chargers does not match the number of EV taxis when the penetration is equal to or greater than 60%, which will affect drivers' charging experience in reality.

Table 5. Peak number of queuing vehicles, finish queuing time, and idle time difference comparison.

EV Taxi Penetration	1st Peak Queue Value	1st Queue Finish Time	Idle EVCS Time Difference
30%	32	14:41	63 min
40%	36	14:45	32 min
50%	44	15:03	33 min
60%	47	16:14	90 min

5. Conclusions

This paper proposes a load forecast method for charging stations based on multi-source information and prospect theory. The following conclusions can be drawn.

(1) The load forecast of EV charging stations considering multi-source information and user decision modification, can avoid inaccurate load forecasts caused by long queues

at charging stations. It can also avoid the behavior of the car owner going to the charging station with a higher electricity price when the charging station is relatively idle, which is more in line with the actual decisions of car owners.

(2) The method proposed in this paper can balance the load of each charging station. On the premise that private cars are charged in residential areas, the ratio between the number of chargers and the number of EVs can be further discussed to avoid excessive vehicle aggregation or a large number of idle chargers.

(3) However, there are still some shortcomings in this paper. For example, the proportion of each influencing factor and reference point in different actual prospect theory decision-making situations of EV users needs to be a personalized adjustment, which will be considered in the following research.

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Appendix A

Table A1. OD matrix at 7:00~17:00 on weekdays.

Departure \Destination	Residence	Work	Business	Special
Residence	0.2	0.55	0.2	0.05
Work	0.2	0.6	0.15	0.05
Business	0.2	0.4	0.4	0
Special	0.2	0.8	0	0

Table A2. OD matrix at 17:00~22:00 on weekdays.

Departure \Destination	Residence	Work	Business	Special
Residence	0.5	0.1	0.4	0
Work	0.6	0.1	0.3	0
Business	0.6	0.1	0.3	0
Special	0.2	0.8	0	0

Table A3. OD matrix at 22:00~7:00 (+1) on weekdays.

Departure \Destination	Residence	Work	Business
Residence	0.8	0.1	0.1
Work	0.8	0.1	0.1
Business	0.7	0.1	0.2

Table A4. Stay time of taxis in different areas on weekdays.

Area \Time(min)	7:00~17:00	17:00~22:00	22:00~7:00 (+1)
Residence	1	1	6
Work	2	1	5
Business	4	2	4
Special	3	0	0

Table A5. Each level of electricity price corresponds to the road node where the charging station is located.

TOU price level	Road node where the EVCS is located
Level 1	18, 21, 22, 31, 43
Level 2	9, 17, 47
Level 3	5, 7, 29, 32

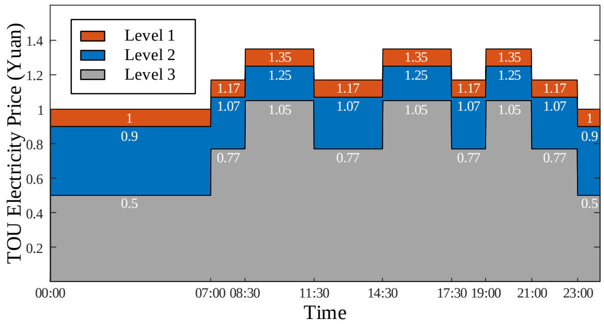

Figure A1. Electricity TOU Price of different EVCSs.

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