IEEE Xplore ®
Notice to Reader

"Dynamic Response Characteristics of Fast Charging Station-EVs on Interaction of Multiple Vehicles" by Xiaoou Liu
DOI: 10.1109/ACCESS.2020.2977460

It is recommended by the Editor-in-Chief of IEEE *Access* that the above-mentioned article should not be considered for citation purposes. IEEE policy requires that consent to publish be obtained from all authors prior to publication.

This paper was submitted by Xiaoou Liu without the consent of co-author Hong Liu, who was the main contributor of the work.

We regret any inconvenience this may have caused.

Prof. Derek Abbott
Editor-in-Chief
IEEE Access

Received February 15, 2020, accepted February 27, 2020, date of publication March 2, 2020, date of current version March 11, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2977460

Dynamic Response Characteristics of Fast Charging Station-EVs on Interaction of Multiple Vehicles

XIAOOU LIU
China Energy Engineering Group Tianjin Electric Power Design Institute Corporation, Ltd., Tianjin 300400, China
e-mail: liuxiaoou126@126.com

ABSTRACT In view of the existing problems that multiple vehicles interaction in the selection of fast charging stations for electric vehicles (EVs) and the equalizing the service capability by multiple stations game in station-EVs interaction, a dynamic response strategy of fast charging station-EVs considering interaction of multiple vehicles is proposed. According to this, the charging scheme of EVs and the dynamic service fee of charging stations are decided. Firstly, the charging guidance framework of station-EVs interaction is proposed to describe the information flow relationship for vehicle, station, road and intelligent transportation system (ITS). Secondly, in order to meet the diversified needs of car owners in charging selection, a charging navigation model is established. Considering the impact of dynamic path travel time, a dynamic path selection model of urban road network is established based on the road segment transmission model. Thirdly, in order to accurately analyze the interaction process between vehicles, a charging decision-making method is proposed considering the dynamic evolution of EVs, which reflects the station selection probability of different positions during driving. Fourthly, according to the queuing time of the charging station, the service fee of the charging station is dynamically adjusted to optimize the service capacity of the charging station, and the multi-agent stackelberg game model is established by combining the charging station selection of EVs with the dynamic service fee of charging station. Finally, Sioux Falls urban road network system is used as an example to analyze the path selection, dynamic decision of charging station selection and service fee, and station-EVs interaction strategy. The results show that this method improves the efficiency of electric vehicle charging station searching, guides EVs in the road network to charge orderly, balances the charging load between charging stations and optimizes the service capacity of charging station reasonably.

INDEX TERMS Fast charging station, navigation, interaction of multiple vehicles, dynamic response, spatial transfer ability.

$d_{ij}^{\mathrm{os}}, d_{ij}^{\mathrm{sd}}$	the length of the road segment ij from the starting position to the charging station and from the charging station to the destination respectively
x_{ij}	0-1 variable
T_{d}	travel time to the charging station
T_{q}	queuing time of EVs in the charging station
T_{c}	charging time
C_{bat}	battery capacity of electric vehicle
SOC_{ini}	initial state of charge
w_e	power consumption per kilometer
$\mathrm{tt}_i(\mathrm{t})$	the travel time of road segment i during period t
tt_i^w	the travel time of road segment i in path w.
$\sigma_{\mathrm{tt},i'}^{w'}$	the standard deviation of the travel time reliability of road segment i' in alternative path w'
$q_{\mathrm{OD}}^w(x,t)$	the traffic flow of path w in OD at time t.
$q_{\mathrm{OD}}(x,t)$	the total traffic flow in OD at time t.
$N_{\mathrm{OD}}(\mathrm{t})$	the number of vehicles in OD at time t.
$N_{\mathrm{OD}}^w(\mathrm{t})$	the number of vehicles driving in path w of OD at time t.
$\alpha_{w'}$	the proportion of vehicles that choose the path w'
Q_{ex}	expected residual capacity at the end of charging

The associate editor coordinating the review of this manuscript and approving it for publication was Md Asaduzzaman.

P	power of charger
η	charging efficiency
$T_c^{s_{re}}$	remaining charging time of the electric vehicle charging on charger S
N_q	set of electric vehicles queuing for charging in line
T_c^s	charging time required for the electric vehicle waiting for charging on charger S
Q_{re}	residual capacity
$N(x, t_0)$, $N(x_0, t)$	the total number of vehicles in position x at t_0 and the total number of vehicles in x_0 at t, respectively.
q_{max}	maximum capacity of the road segment
ρ_{jam}	the blocking density of the road segment
w	reverse shock velocity of the road segment
v_i^{free}	free flow speed of road segment
ρ_i^{min}, ρ_i^{max}	minimum density and maximum density of road segment i.
v_i^{min}	minimum driving speed of vehicles.
Y_i^k	the driving power consumption cost on the road, when electric vehicle k selects the charging station i.
γ	the distance cost coefficient
w_e	the power consumption per kilometer. p_i is the unit service fee of charging station i
α_π	the time cost coefficient
β_π	the service fee price coefficient.
$P_i(t)$	the probability of selecting charging station i.
$\bar{\pi}(t)$	the average payment of the population.
T_q^{avg}	the average queuing time of all charging stations.
C_s	the fixed investment cost of charging station.
C_f^j	the staff salary of charging station j.
C_h^j	the land rent of charging station j.
G_j	the revenue of charging station j
Δp_j	the change of service fee.
s_{jin}, s_{jout}	respectively represent increase and decrease in quantity of vehicles that select charging station j due to the price adjustment.

I. INTRODUCTION

A. MOTIVATION

In order to promote the implementation of energy conservation and emission reduction policies and the development of new energy automobile industry, countries around the world have introduced a timetable for banning the sale of fuel vehicles in [1]. For the vehicles whose driving time is much longer than the stopping time, fast charging is an important way. Large scale disordered charging of electric vehicles will cause serious congestion of charging stations in the core area of the city, and further increase the load of power grid in this area, such as in [2] and [3]. Therefore, through the reasonable scheduling of EVs with fast charging demand, the contradiction between the strong charging demand and the limited charging stations in the local area can be reconciled, the orderly charging of EVs and the service capacity optimization of charging stations can be realized.

B. RELATED WORKS

(1) Background and related works of interactive research on charging stations and EVs

With the development of communication technology, the information between electric vehicle and charging station has two-way flow characteristics, which promotes the station-EVs interaction. In [4], a fast charging navigation strategy for electric vehicles based on the internet of things is proposed. The charging station makes the fast charging price according to the charging power regulation scheme, and the electric vehicle selects the charging station according to the charging price. Reference [5] proposes a stochastic resource planning scheme of charging stations, and considers the impact of price sensitive and scheduled charging electric vehicle users on the service capacity of charging station respectively to optimize the supply side and demand side of electric energy. Reference [6] proposes a hierarchical game method. In the upper level game, a non cooperative game model is established to simulate the competition between electric vehicle charging stations. In the lower level game, the station selection strategy of electric vehicle is formulated based on the pricing strategy.

(2) Background and related works of EVs charging path selection

Due to the influence of the travel habits of electric vehicle users and the urban spatial structure, the charging load will be concentrated in some charging stations during the peak period, which has a great impact on the operation of the power grid and the charging experience of the owners. Therefore, it is necessary to use the charging navigation system to guide the charging of electric vehicles. All infrastructure networks, especially urban areas are highly dependent on the electric grid power-supply [7] analyzed the capacity of the grid to meet large adoption of PHEVs, modelled the interdependency between the power systems and the electrified transportation networks and the Plug-in Electric Vehicles (PEVs) served as coupling agents to realise the interdependencies of the power and transportation networks. In [8] and [9], the driving path of electric vehicle is simulated by Markov state transition analysis method, and the time-space transfer model of charging load is established. In [10]–[13], Agent-cellular automata system is introduced to simulate the behavior of electric vehicle drivers, and the rules of macro traffic flow are obtained by using the data obtained from micro traffic simulation, and then the dynamic evolution process of space-time distribution of electric vehicles is obtained. In [14], taking the total charging time and charging cost as two objectives, a fast charging navigation scheme is obtained based on the constraints of traffic network and distribution network. References [15]–[17] transform driving time and queuing time in charging station into the travel cost of the user, and establishs the charging navigation optimization model aiming at the minimum sum of the travel cost and the charging cost of users. References [18]–[20] study the influence of charging demand on the interests of electric vehicle users, power grid enterprises, charging station operators and transportation departments, and establishs a win-win coordinated charging navigation mode based on the fuzzy decision method. In [21]–[23], combining the travel chain analysis method and Monte Carlo simulation, the travel model of electric vehicle users is established, and the closed-loop simulation is carried out in the way of equal step clock propulsion to complete the time sequence interaction analysis of travel and charging demand. Considering the real-time information interaction between electric vehicle and traffic information center, an electric vehicle navigation system is proposed in [24] based on autonomic computing and vehicle self-organizing network layered architecture, including the traffic and charging station situation prediction and path planning. To decrease the traveling cost of EVs and improve the load level of the concerned distribution system, a dynamic EV charging navigation strategy was proposed based on periodic traffic information update in [25], which can lead to severe congestions in cellular networks and extremely increase communication expense with the dramatic rise of EV number. In the above references, the shortest distance, the minimum time, the smallest time utilization deviation and power utilization deviation of the charging station are taken as objectives, and a multi-objective optimization model for EVs charging path is established.

(3) Background and related works of charging station service fee dynamic decision

As a kind of movable load, electric vehicle has flexible demand response characteristics in a certain space. The reasonable service fee scheme of charging station is beneficial to reduce the charging cost of users and improve the service capacity of charging station. In [26], the pricing strategy of electric vehicle fast charging station is studied. Considering the total revenue of fast charging station and the response of users to the pricing scheme, the pricing scheme of each charging station is optimized to minimize the total voltage amplitude deviation of distribution network. In [27]–[30], aiming at the accessible load threshold of the fast charging station, a charging price formulation method is proposed to guide the electric vehicle to select the idle charging station, which meets the multiple demands of vehicle-station-network. In [31], aiming at the adjustable characteristics of electric vehicle charging demand, a charging price is made to distinguish the busy degree of charging station, which can motivate users to adjust the charging time, so as to improve the charger utilization rate and reduce the queuing time in charging station.

However, in the study of EV charging navigation and Station-EVs interaction, the above references pay more attention to modeling from the perspective of single vehicle, which is not enough to reflect the interactive influence of charging station selection among a large number of electric vehicles. In the research of station-EVs interaction, the traditional charging pricing mostly considers the control of users' charging behavior, without considering the influence of price game between multiple stations on equalizing the load of charging stations.

C. CONTRIBUTION

In this paper, a dynamic response strategy of electric vehicle and fast charging station considering the interaction of multi-vehicle is presented. The list of key contributions are as follows.

(1) Based on the analysis of the dynamic evolution process of vehicles, from the three aspects of distance, total charging time and service fee, this paper puts forward EV charging navigation schemes.

(2) Based on the dynamic path selection model, the dynamic traffic simulation method of urban road network is proposed, the dynamic travel time is obtained, and the selection of vehicle driving path schemes is realized.

(3) By using the method of multi-agent stackelberg game, the dynamic service fee of charging station is established, the orderly charging of EVs and the service capacity optimization of charging stations can be realized.

D. ORGANIZATION

In this context, based on the intelligent transportation system, Part II proposes a framework of supply and demand interaction between fast charging station and electric vehicle. In Part III, considering the interaction of vehicles with charging demand in the driving process, the dynamic path selection model of electric vehicles is established, the charging navigation strategy of vehicle dynamic evolution is proposed, and the charging scheme is decided. In Part IV, combined with the demand response characteristics of electric vehicle owners and the service capacity of charging station, a dynamic service fee model of charging station is proposed based on multi-agent stackelberg game model, which describes the interaction process between the service fee adjustment of charging station and the dynamic charging station selection of users, guides users to charge in idle fast charging station, and realizes the spatial transfer of load. Finally, a certain typical city is taken as an example to verify the effectiveness of the method in Part V.

II. FRAMEWORK DESCRIPTION OF THE DYNAMIC RESPONSE STRATEGY OF FAST CHARGING STATION-EVS

With the development of 5G communication, the intelligent transportation system (ITS), which is supported by the vehicular networking technology, is becoming more and more mature in Vehicle-to-Infrastructure cooperation. At the same time, edge computing technology also provides users with a high reliability and low delay operation environment, such as in [32]. Without central scheduling node, it is possible to realize information sharing and transmission between vehicles, stations, roads and ITS.

In the future, the electric vehicle can be connected with the vehicular networking platform system (VNPS) through the internet to upload the status and location of the electric

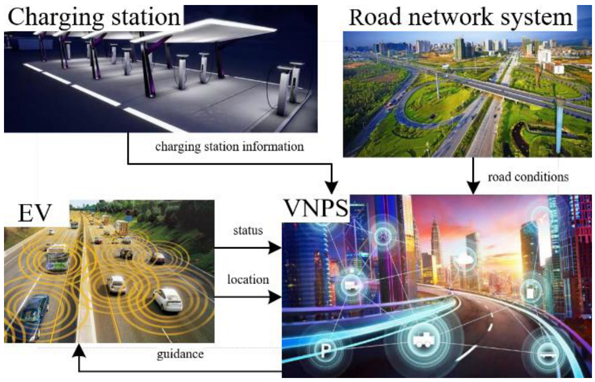


FIGURE 1. EV charging charging guidance system framework.

vehicle in real time. At the same time, electric vehicles can also get the current information of the road conditions and the charging station operation. Through the analysis of the electric vehicle status, VNPS can predict the charging demand and the charging time of the electric vehicle, so as to predict the road condition and the charging station condition at the charging time.

The structure of the electric vehicle charging guidance system is shown in Fig.1. With VNPS as the center, the road condition information is dynamically updated to promote station-EVs interaction. Each EV independently interacts with VNPS.

Through the research of the Section III, the following goals can be realized. After the electric vehicle sends out the charging request, without considering he influence of communication delay and according to the vehicle travel demand, VNPS recommends the charging strategy to the owner from the shortest distance, the minimum time or the lowest cost. The owner chooses the most effective charging station for himself and get the optimal path to charge, according to the geographical location, destination location, road condition information and the queuing time in each charging station at the moment. Every certain time, the traffic flow information and charging station information will be refreshed, and the optimal charging station is recalculated and the driving path is replanned.

Through the research of the Section IV, the following goals can be realized. According to the maximum transmission power that can be obtained from the distribution network at the moment, the charging station calculates the number of vehicles that can be accepted in this period. Based on the service fee of surrounding charging station obtained from VNPS and the charger utilization rate, the charging station formulates the service fee in this period considering its own profitability and uploads the service fee to VNPS. VNPS publishes the information to the EV users with charging request, and updates the queuing time of EVs in each charging station to dynamically adjust the deployment of charging vehicles to each charging station. For electric vehicle users with high price elasticity, if the service fee is higher than the price sensitivity threshold, it will prompt users to change the charging station selection in response to the price signal of the charging station, and the spatial transfer of charging load is realized.

III. VEHICLE DECISION SCHEME CONSIDERING CHARGING NAVIGATION AND DYNAMIC TRAFFIC SIMULATION

Electric vehicle charging navigation is an important means to achieve coordinated charging. Customized navigation scheme for different vehicle charging needs can effectively improve the response of car owners. Taking a single vehicle as the research object, the electric Vehicle Charging Navigation Model is established considering the three factors of distance, total time or economy in Section A of Part III. The travel time in the total time is detailed in Section B of Part III. The three factors are also the basis for analyzing the charging station selection under the interaction of multiple vehicles in Section C of Part III.

Dynamic traffic simulation method of urban road network is proposed in Section B of Part III to calculate the travel time, simulate the driving behavior of vehicle owners, and establish a dynamic path selection model to analyze the interaction between vehicles driving on the road, so as to provide transportation support for the EV charging decision.

Based on the electric vehicle charging navigation model in Section A of Part III and the dynamic path selection model in Section B of Part III, multi-vehicles charging selection method considering decision dynamic evolution is proposed in Section C of Part III.

A. ELECTRIC VEHICLE CHARGING NAVIGATION MODEL

Assume the electric vehicle is driving on the road, when its residual capacity is lower than the threshold or not enough to reach the destination, it will generate fast charging demand. The charging navigation model needs to consider the driving distance, the total driving and charging time and the charging economy.

When some electric vehicle owners can not access VNPS for some reason, they can not obtain real-time road condition and charging station information. Such owners usually choose the nearest charging station for charging. Dijkstra algorithm is used to calculate the shortest path in this paper. The direction of charging station selection should be consistent with the direction to the destination, i.e. no turning back. Therefore, the path optimization is carried out with the shortest sum of the distance O from the starting point to the charging station and the distance D from the charging station to the destination as the objective.

$$\min S = \sum_{i=1}^{m} \sum_{j=1, j\neq i}^{n} d_{ij}^{\mathrm{os}} x_{ij} + \sum_{i=1}^{m} \sum_{j=1, j\neq i}^{n} d_{ij}^{\mathrm{sd}} x_{ij} \tag{1}$$

In formula, i, j are the road network nodes. m, n are the total number of road network nodes. d_{ij}^{os}, d_{ij}^{sd} are the length of the road segment ij from the starting position to the charging station and from the charging station to the destination respectively. x_{ij} is 0-1 variable. If the road segment ij is selected, $x_{ij} = 1$, otherwise $x_{ij} = 0$.

For users who can access VNPS, if they have high time sensitivity, they should optimize the charging path aiming at the shortest total charging time.

$$\min T = T_\mathrm{d} + T_\mathrm{q} + T_\mathrm{c} \tag{2}$$

In formula, T_d is the travel time to the charging station. T_q is the queuing time of EVs in the charging station. T_c is the charging time.

When the electric vehicle reaches the charging station, the residual capacity Q_re is directly related to the distance that it drives on the road, as shown in equation (3).

$$Q_\mathrm{re} = C_\mathrm{bat} \cdot SOC_{ini} - w_e \int_0^{T_d} v_i \mathrm{d}t \tag{3}$$

In formula, C_bat is the battery capacity of electric vehicle. SOC_{ini} is the initial state of charge. w_e is the power consumption per kilometer.

Assume that the charging power of the charger in the charging station is constant, T_c can be expressed as equation (4).

$$T_\mathrm{c} = (Q_\mathrm{ex} - Q_\mathrm{re})/P\eta \tag{4}$$

In formula, Q_ex is the expected residual capacity at the end of charging, which is set to 90% of battery capacity in [33]. P is the power of charger. η is the charging efficiency.

T_q depends on the sum of the power demand of the vehicles queuing in front, which changes with the change of the queue length, as shown in equation (5).

$$T_\mathrm{q} = T_\mathrm{c}^{S_{re}} + \sum_{l_s \in N_\mathrm{q}} T_\mathrm{c}^{s} \tag{5}$$

In formula, $T_\mathrm{c}^{S_{re}}$ is the remaining charging time of the electric vehicle charging on charger S. l_s is the electric vehicle to be charged on charger S soon. N_q is the set of electric vehicles queuing for charging in line. T_c^{s} is the charging time required for the electric vehicle waiting for charging on charger S.

Some users connected to VNPS are more sensitive to the travel cost. The travel cost C includes the driving power consumption cost on the road C_road and the charging cost in charging station C_ch. The optimization model is established to minimize the travel cost as follow.

$$\begin{aligned} \min C &= C_{road} + C_\mathrm{ch} \\ &= \bar{\rho} w \int_0^{T_d} v_i \mathrm{d}t + P \int_{t_{start}+T_d+T_q}^{t_{start}+T} \rho(t) dt \end{aligned} \tag{6}$$

In formula, $\bar{\rho}$ is the average value of EV fast charging price. P is the fast charging power provided by the charging station to the EV. t_{start} is the moment of EV departure from the start point. $\rho(t)$ is the fast charging price of charging station, including the spot price and charging service fee.

The premise of selecting charging station for electric vehicle is that its residual capacity Q_re should be able to maintain its arrival at charging station, and it should meet the residual capacity constraint as follow.

$$Q_\mathrm{re} > w_e{}^* d^{os} \tag{7}$$

B. DYNAMIC TRAFFIC SIMULATION OF URBAN ROAD NETWORK

In the urban road network, the driving behaviors of vehicle owners are quite different. The spatial-temporal distribution of vehicles presents obvious random characteristics. Therefore, the travel time of the road segment T_d is also time-varying. Based on the theory of dynamic traffic simulation in [34]–[37], this paper proposes a dynamic travel time model, and then analyzes the traffic characteristics of urban road network.

Due to the characteristics of high density and less dead end roads in urban road network, there will be multiple paths for car owners to choose under the condition of given starting and ending points. Based on the dynamic travel time, this paper establishes a path selection model to describe the driving characteristics of vehicle owners.

1) DYNAMIC TRAVEL TIME MODEL OF ROAD SEGMENT

The dynamic traffic simulation method in this paper is based on the road segment transfer graph model in [37], which includes the road segment model and the node model, in which the node is the boundary of the road segment. The movement of vehicles in the road segment can be described by the cumulative number of vehicles $N(x, t)$, which represents the number of vehicles passing through the observation point x before time t. For each road segment, it is necessary to ensure that the vehicle meets the first in, first out (FIFO) rule.

According to the definition of traffic flow and density, the traffic flow $q(x, t)$ and traffic flow density $\rho(x, t)$ are obtained as follow.

$$\begin{cases} q(x,t) = \lim\limits_{t \to t_0} \dfrac{N(x,t) - N(x,t_0)}{t - t_0} = \dfrac{\partial N(x,t)}{\partial t} \\ \rho(x,t) = \lim\limits_{x \to x_0} \dfrac{N(x_0,t) - N(x,t)}{x - x_0} = -\dfrac{\partial N(x,t)}{\partial x} \end{cases} \tag{8}$$

In formula, $N(x, t_0)$ and $N(x_0, t)$ are the total number of vehicles in position x at t_0 and the total number of vehicles in x_0 at t, respectively.

The three parameters of traffic flow include flow, density and speed. According to the relationship among them, the free flow speed v^free is calculated as follow.

$$v^\mathrm{free}(x,t) = q(x,t) \big/ \rho(x,t) \tag{9}$$

Given the maximum capacity q_max and the blocking density ρ_jam of the road segment, the critical density ρ_crit and the reverse shock velocity w of the road segment can be expressed as follow.

$$\begin{cases} \rho_{crit} = q_\mathrm{max} \big/ v^\mathrm{free} \\ \omega = -q_\mathrm{max} \big/ \left(\rho_\mathrm{jam} - \rho_{crit}\right) \end{cases} \tag{10}$$

Assuming that the free flow vehicles are evenly distributed in the road segment, the density ρ_i(t) of road segment i can be expressed as follow.

$$\rho_i(\mathrm{t})=\max\{x_i(t)+N(x_i^0,t)-N(x_i^L,t),0\}\Big/L_i \tag{11}$$

In formula, x_i(t) is the number of vehicles in road segment i during period t. n_i is the number of vehicles that can be accommodated in unit length of road segment i. L_i is the length of road segment i.

After the density of traffic flow is obtained, according to the speed-density function, the driving speed v_i(t) of road segment i can be expressed as follow.

$$v_i(t)=\begin{cases} v_i^{\mathrm{free}} & \rho_i(t)<\rho_i^{\min} \\ v_i^{\min}+(v_i^{\mathrm{free}}-v_i^{\min})\times & \rho_i(t)\in \\ (1-(\dfrac{\rho_i(t)-\rho_i^{\min}}{\rho_i^{\max}-\rho_i^{\min}})^{\alpha})^{\beta} & [\rho_i^{\min},\rho_i^{\max}] \\ v_i^{\min} & \rho_i(t)>\rho_i^{\max} \end{cases} \tag{12}$$

In formula, v_i^{free} is the free flow speed of road segment. $\rho_i^{\min}$ and $\rho_i^{\max}$ are the minimum density and maximum density of road segment i. $v_i^{\min}$ is the minimum driving speed of vehicles. α and β are model parameters.

Therefore, the travel time tt$_i$(t) of road segment i during period t can be expressed as follow.

$$\mathrm{tt}_i(t)=L_i/v_i(t) \tag{13}$$

2) DYNAMIC PATH SELECTION MODEL

Due to the characteristics of high density and less dead end roads in urban road network, there will be multiple paths for EV owners to select under the condition of given starting and ending points. Therefore, based on the dynamic travel time, this section establishes a dynamic path selection model to describe the driving characteristics of EV owners.

It is assumed that each vehicle owner selects the shortest time path to the destination pre-trip, and changes the path to reduce the delay time after receiving the congestion information of the road segment during the trip. The subjective probability that alternative road segment i' is selected is shown in equation (14).

$$P_{i'}^{w'}(0<\mathrm{tt}_{i'}^{w'}\le \mathrm{tt}_i^{w})=\frac{1}{\sqrt{2\pi}\sigma_{\mathrm{tt},i'}^{w'}}\int_0^{\mathrm{tt}_s^{w}} e^{-\frac{(\mathrm{tt}-\mathrm{tt}_{i'}^{w'})^2}{2(\sigma_{\mathrm{tt},i'}^{w'})^2}}\mathrm{d}(\mathrm{tt}) \tag{14}$$

In formula, $\mathrm{tt}_{i'}^{w'}$ is the travel time of road segment i' in alternative path w'. tt_i^{w} is the travel time of road segment i in path w. $\sigma_{\mathrm{tt},i'}^{w'}$ represents the standard deviation of the travel time reliability of road segment i' in alternative path w'.

The actual path chosen by the car owner, which shall meet the shortest travel time, is the path with the largest subjective probability, as shown in equation (15).

$$P_i^{w'}=\max(P_i^{w_1},P_i^{w_2},\cdots,P_i^{w_n}) \tag{15}$$

At time t, the calculation method of traffic flow on different paths of OD interval is shown in equation (16).

$$q_{\mathrm{OD}}^{w}(x,t)=q_{\mathrm{OD}}(x,t)N_{\mathrm{OD}}^{w}(\mathrm{t})/N_{\mathrm{OD}}(\mathrm{t}) \tag{16}$$

In formula, $q_{\mathrm{OD}}^{w}(x,t)$ is the traffic flow of path w in OD at time t. $q_{\mathrm{OD}}(x,t)$ is the total traffic flow in OD at time t. N_{OD}(t) is the number of vehicles in OD at time t. N_{OD}^{w}(t) is the number of vehicles driving in path w of OD at time t.

Due to the congestion in the road segment i of OD, some vehicles passing through road segment i will choose to bypass to other road segment, and the remaining number of vehicles entering the road segment i $\bar{N}_{\mathrm{OD}}^{w}(t)$ is shown in equation (17).

$$\bar{N}_{\mathrm{OD}}^{w}(t)=\sum_{x\in i}q_{\mathrm{OD}}^{w}(x,t)-kq_{\mathrm{OD}}(x,t)N_{\mathrm{OD}}^{w_i}(t)\Big/N_{\mathrm{OD}}(t) \tag{17}$$

In formula, k represents the proportion of vehicles changing the path due to the road segment congestion. $N_{\mathrm{OD}}^{w_i}(t)$ is the number of vehicles driving in road segment i at time t.

There are multiple alternative paths for vehicle owners who change the path. The number of vehicles $N_{\mathrm{OD}}^{w'}(t)$ allocated to the path w' is shown in equation (18).

$$N_{\mathrm{OD}}^{w'}(t)=k\alpha_{w'}q_{\mathrm{OD}}(x,t)N_{\mathrm{OD}}^{w_i}(t)\Big/N_{\mathrm{OD}}(t) \tag{18}$$

In formula, $\alpha_{w'}$ is the proportion of vehicles that choose the path w', among the vehicle owners who change the path, $0\le \alpha_{w'}\le 1$.

Through the calculation of travel time and the construction of path selection model, we can get the result of dynamic traffic flow distribution, and determine the complete dynamic travel path of vehicles.

C. MULTI-VEHICLES CHARGING SELECTION CONSIDERING DECISION DYNAMIC EVOLUTION

After VPNS recommends the charging strategy to the electric vehicle users, the users will not necessarily charge according to the recommended scheme, and there will be the uncertainty of choice.

The charging selection of multiple electric vehicles is a game problem, and the participants of the game are the whole of N electric vehicles with charging demand in the road network. After receiving the status information of the charging station from VPNS, each EV user selects a charging station for charging. Due to personal privacy and other factors, car owners cannot see the charging station selected by other users on VPNS. Thus, the problem can be transformed into a hybrid strategy problem to solve. Mixed Logit model is the most general discrete choice model, which can deal with the problem of consumer choice with random preference difference. In the case of random preference differences, the probability of the owner's initial charging station selection P_i can be described as follow.

$$P_i=\int L_i(\beta)f(\beta\,|\theta\,)d\beta=\int(\frac{e^{-(\beta\pi_i)}}{\sum\limits_{i\in M}e^{-(\beta\pi_i)}})f(\beta\,|\theta\,)d\beta \tag{19}$$

In formula, β is the preference difference of charging station selection. π_i is the utility value. M is the set of all charging stations.

Because the probability function of this mixed Logit model is unclosed-form, it can not be solved by analytical method. Monte Carlo sampling method can be used to discretize the integral and approximately solve the probability function of continuous random variables. The process is as follows.

Step 1, the maximum likelihood estimation method is used to estimate the parameter θ.

Step 2, after θ determined, a random variable β is randomly selected from the given density function $f(\beta|\theta)$.

Step 3, calculate the probability value P_i according to the equation (19).

Step 4, repeat sampling N' times and calculate the mean probability value of station selection $P_i(\beta)$, which can be expressed as follow.

$$P_i(\beta) = \sum\nolimits_{n=1}^{N'} L_i(\beta^n) \Big/ N' \tag{20}$$

In the process of electric vehicle driving to the charging station, the queuing time and charging service fee of the charging station may be dynamically adjusted at any time. Therefore, the choice of charging station for electric vehicles will also change. When one car owner changes his decision, it will certainly have an impact on the decision of other car owners. Therefore, the adjustment of decision is essentially a process of evolutionary game. The payment function of charging station selection π can be expressed as follow.

$$\begin{aligned}\pi &= -Y_i^k - \alpha_\pi(T_{\mathrm{q}}^j + T_{\mathrm{d}}) - \beta_\pi p_i^2 \\ &= -\gamma d_i^k - \alpha_\pi(T_{\mathrm{q}}^j + T_{\mathrm{d}}) - \beta_\pi p_i^2 \\ &= -p_i w_e d_i^k - \alpha_\pi(T_{\mathrm{q}}^j + T_{\mathrm{d}}) - \beta_\pi p_i^2\end{aligned} \tag{21}$$

In formula, Y_i^k is the driving power consumption cost on the road, when electric vehicle k selects the charging station i. γ is the distance cost coefficient. w_e is the power consumption per kilometer. p_i is the unit service fee of charging station i. d_i^k is the distance between electric vehicle k and charging station i. α_π is the time cost coefficient, a reference range of time cost coefficient is given as 17-22¥ /h in [38]. β_π is the service fee price coefficient.

As a rational decision-maker, EV users have certain learning and imitation ability for the optimal strategies in the group. The replicator dynamic model can be established as follows.

$$\frac{\partial P_i}{\partial t} = P_i(t)[\pi_i(t) - \bar{\pi}(t)] \tag{22}$$

$$\bar{\pi}(t) = \sum_{i \in M} P_k(t)\pi_k(t) \tag{23}$$

In formula, $P_i(t)$ is the probability of selecting charging station i. t is the time. $\bar{\pi}(t)$ is the average payment of the population.

According to the characteristics of the differential equation (22), the faster the individual with the optimal response can obtain the optimal charging strategy. When there is no difference between the user's payment function π and the average payment of the population $\bar{\pi}(t)$, it is considered that the evolution has reached an equilibrium point, as shown in equation (24).

$$\frac{\partial P_i}{\partial t} = 0 \tag{24}$$

At t_0, when any EV owner changes the target charging station and its payment function value is lower than that of the original strategy, which indicates that there is no interest in its change strategy, and the evolution process is terminated. The solution of evolution process can be approximated by discrete steps, as shown in equation (25).

$$P_i(s+1) = P_i(s) + \Delta \times P_i(s) \times [\pi_i(s) - \pi_i(s)] \tag{25}$$

In formula, s is the number of iterations. is the step size in simulation.

Due to the continuous change of space-time position in the process of electric vehicle driving, the probability of charging station selection is also changing dynamically. The influence on the probability of charging station selection is still analyzed by the factors of distance, time and price in Section B of Part III.

Generally, when the electric vehicle passes or is close to a charging station, if which is not selected, the chosen probability of the charging station in the following time will be reduced rapidly. In this paper, the exponential function model is used to describe this feature as follows.

$$P_i = \begin{cases} 1/N_s & x < d_{\mathrm{o}1} \\ \dfrac{1/e^{d_i}}{\sum\limits_{i \in M} 1/e^{d_i}} & x \geq d_{\mathrm{o}1} \end{cases} \tag{26}$$

$$d_i = \max\{d_{\mathrm{OD}}, d_{OD} + 2(x - d_{oi})\} \tag{27}$$

In formula, d_i is the distance between the vehicle and charging station i. x is the distance traveled. $d_{\mathrm{o}1}$ and d_{oi} are the distance traveled from the starting point to the first charging station and the charging station i respectively. d_{OD} is the total length of the travel.

Considering the influence of travel time and queuing time on station selection, the probability function can be expressed as follow.

$$P_i(T_{\mathrm{d}}, T_{\mathrm{q}}) = \frac{1}{\|d_{oi} - x\|} \times \frac{1}{T_d + T_q^i} \Bigg/ \left(\sum_{i \in M} \frac{1}{\|d_{oi} - x\|} \times \frac{1}{T_d + T_q^i}\right) \tag{28}$$

For charging stations with different service fee, if the charging cost of low unit price plus the detour time cost is still lower than the charging cost of high unit price, the price sensitive users will choose detour to charging, and the SOC consumption in both scenarios is shown in Fig.2.

Therefore, from the perspective of price, the probability expression of selecting charging station is shown as

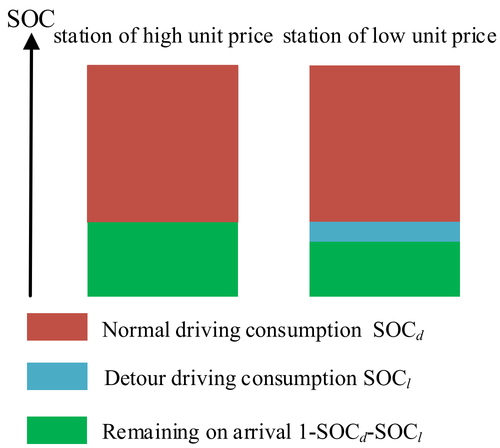


FIGURE 2. SOC consumption situation in different scenarios.

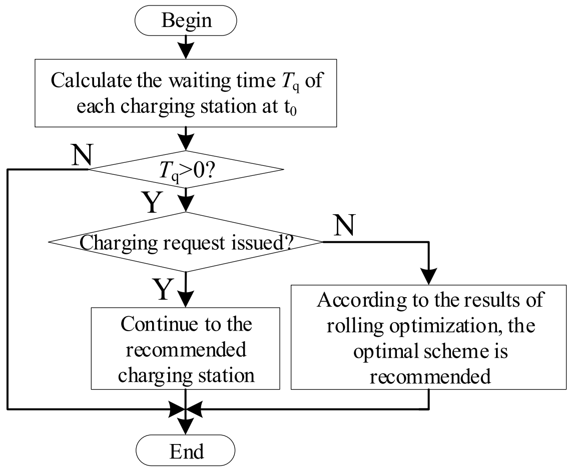


FIGURE 3. Charging recommendation process of VNPS.

equation (29).

$$P_i = \frac{1/e^{p_i}}{\sum_{i \in M} 1/e^{p_i}} \tag{29}$$

IV. STATION-EVS INTERACTION STRATEGY BASED ON THE STACKELBERG GAME

After obtaining the charging selection of electric vehicles, the charging station shall guide the electric vehicles in the road network to charge orderly according to the actual situation in the station, and optimize the service capacity of charging station reasonably.

A. SERVICE CAPACITY OPTIMIZATION MODEL OF CHARGING STATION

There are many fast charging stations in the urban area. The function of charging stations is similar, and there is obvious substitution relationship between them. The VNPS can update the status of each charging station in real time, optimize the charging recommendation strategy issued to car owners, and improve the charger utilization rate of idle charging station.

Combined with the charger utilization of each charging station and the number of vehicles in the station, an optimization method is used to minimize the variance of queuing time between charging stations.

$$\min F = \frac{1}{N_s} \sum_{t=t_0+1}^{T} \sum_{i=1}^{N} (T_q^i - T_q^{avg})^2 \tag{30}$$

In formula, N_s is the number of charging stations in the area. t_0 is the number of current scheduling time. T is the total number of scheduling time interval, 15 minutes is a scheduling time interval, one day is divided into 96 scheduling time intervals. T_q^i is the queuing time of charging station i. T_q^{avg} is the average queuing time of all charging stations.

T_q^{avg} is affected by the power demand of charging vehicles and queuing vehicles. The longer the remaining time of charging vehicles or the larger the power demand of queuing vehicles, the longer the queuing time. Assuming current time is t_0, T_q^{avg} can be expressed as follow.

$$T_q^{avg} = \frac{1}{\eta N_s P} \sum_{i=1}^{N_s} \left[\sum_{j=1}^{m_i} (Q_{ex} - Q(t_0)) + \sum_{j=m_i+1}^{k_i} (Q_{ex} - Q_{re}) \right] \tag{31}$$

In formula, m_i and k_i are the number of chargers and electric vehicles in charging station i respectively.

If a large number of electric vehicles queuing for charging are piled up in a charging station at t_0, the number of electric vehicles it can serve at t_0+1 will be affected. Assuming that VNPS distributes the charging demand in accordance with the service capacity of the charging station, the charging demand $Q_i(t_0+1)$ that can be recommended to the charging station i at t_0+1 is shown as follow.

$$Q_i(t_0+1) = [Q^q(t_0) + Q(t_0+1)] \cdot \frac{P_i}{P} - Q_i^q(t_0) \tag{32}$$

In formula, Q_i^q is the demand power of electric vehicles queuing at charging station. P_i is the total charging power of charging station i.

When $Q_i(t_0+1)$ is negative, the VNPS will not recommend new charging demand to charging station i temporarily. For the electric vehicles with and without charging request, the overall process recommended by VNPS is shown as Fig.3.

B. STATION-EVS STACKELBERG GAME MODEL

Due to the uneven distribution of charging vehicles in each charging station, the node voltage of distribution network will be reduced, the network loss will be increased, and the reliability will be reduced, such as in [17], [39]–[41]. Through the price setting, some price sensitive car owners can be guided to the charging station with low service fee.

In the peak load period, a large amount of electric vehicles charging at the same time may cause the node voltage not to meet the requirement in [42], then the service fee of charging station can be increased to reduce the fast charging load of electric vehicles. On the other hand, in some areas with smaller traffic flow, there are less electric vehicles in these charging stations, which can attract more electric vehicles to charge by reducing service fee and improve the charger utilization rate.

While adjusting the service fee, the charging station should consider cost constraints to maintain its sustainable operation. The cost of charging station j usually includes construction cost and operation cost. The equivalent annual value of construction cost C_{con}^{j} is shown in equation (33).

$$\begin{aligned} C_{con}^{j} &= (\lambda \cdot m_j + C_s)\frac{i(1+i)^n}{(1+i)^n - 1} \\ &= (\lambda \cdot m_j + a_s\varphi_1)\frac{i(1+i)^n}{(1+i)^n - 1} \end{aligned} \tag{33}$$

In formula, λ is the construction cost of a single charger. m_j is the number of chargers at charging station j. C_{s} is the fixed investment cost of charging station. i is the annual interest rate. n is the service life. a_s is the area of charging station j. φ_1 is the construction cost per unit area of charging station j.

The operation cost of the charging station C_{o}^{j} mainly includes labor cost and land rent, which can be expressed as equation (34).

$$C_{\mathrm{o}}^{j} = C_{\mathrm{f}}^{j} + C_{\mathrm{h}}^{j} = C_{\mathrm{f}}^{j} + a_s\varphi_2 \tag{34}$$

In formula, C_{f}^{j} is the staff salary of charging station j. C_{h}^{j} is the land rent of charging station j. φ_2 is the land price per unit area where the charging station j is located The closer to the city center, the more expensive C_{h}^{j} is.

The charging station has the authority to change the charging service fee. The electric vehicle users get the service fee information of each charging station published on VNPS, and select the station that can maximize their own interests. The charging station can adjust the service fee according to the number of electric vehicles in the station. The above is essentially a stackelberg game problem. Considering the bipartite game subjects, one is the set of charging stations, which strategy is the formulation of dynamic service fee, and the other is the set of electric vehicles with charging demand, which strategy is the charging station selection. As the leader of the game, the charging stations formulate the service fee to guide the electric vehicle.

Because the service between charging stations is alternative, this paper focuses on the analysis of the stackelberg game in which multiple charging stations influence each other. Charging stations should consider not only the behavior of electric vehicle users, but also the behavior of other charging stations, and conduct multi-agent stackelberg game. The utility function G_j is to maximize charging station revenue by adjusting the service fee, which can be decided by charging station.

$$\begin{aligned} \max G_j = (p_j - \Delta p_j)[\sum_{i=1}^{n} D_i + (\sum_{i=1}^{s_{jin}} D_i - \sum_{i=1}^{s_{jout}} D_i)] \\ - a(C_o^j + C_{con}^j/365) \end{aligned} \tag{35}$$

In formula, G_j is the revenue of charging station j. Δp_j is the change of service fee. D_i is the charging demand of electric vehicle i. n is the number of electric vehicles that have not changed the charging selection after the price adjustment. s_{jin} and s_{jout} respectively represent increase and decrease in quantity of vehicles that select charging station j due to the price adjustment. a is the cost coefficient of charging station in a period.

The service fee needs to meet the constraints of national macro policy in [43].

$$p_j < \mathrm{r} \tag{36}$$

In formula, r is the upper limit of service fee.

The owner selects the charging station according to the charging price published by VNPS, and the utility function π_i is to maximize their own interests as follow.

$$\max \pi_i = -(p_j - \Delta p_j)[Q_{\mathrm{ex}} - Q_{\mathrm{re}} + w \cdot d_{jd}] - \alpha \cdot (T_{\mathrm{q}}^{j} + T_{\mathrm{d}}) \tag{37}$$

In formula, d_{jd} is the distance from the charging station j to the destination.

In this game, equilibrium refers to a kind of strategy set $c^* = \{c_1^*, \ldots, c_n^*\}$ that all participants can get the maximum benefit. Each participant can always get the maximum benefit when compared with other strategies. Therefore, all participants have no motivation to deviate from the equilibrium strategy. For each participant i, the following constraint need to be met.

$$\pi_i(\mathrm{c}_i^*, \mathrm{c}_{-i}) \geq \pi_i(\mathrm{c}_i, \mathrm{c}_{-i}), \quad \forall i \in N^i \tag{38}$$

In formula, c_{-i} is a set of participants except participant i.

The existence proof of the equilibrium solution of this game is shown as follow. Assuming that the electricity sales of charging station j is Q_j, the total electricity sales of all charging stations is $Q = Q_1 + \ldots + Q_{\mathrm{Ns}}$, the function of price p_j can be expressed as $p_j = f(Q_1, \ldots, Q_{\mathrm{Ns}})$, and $Q_j = f^{-1}(p_1, \ldots, p_{\mathrm{Ns}})$. The income of charging station j is $G_j = Q_j{}^* f(Q_1, \ldots, Q_{\mathrm{Ns}})$. To maximize G_j, the first-order condition must be met as follow.

$$\frac{\partial G_j}{\partial Q_j} = f(Q_1, \cdots, Q_{\mathrm{N}}) + Q_j \frac{\mathrm{d}f(Q_1, \cdots, Q_{\mathrm{N}})}{\mathrm{d}Q_j} = 0 \tag{39}$$

At the same time, the first-order condition of the electricity sales of charging station j shall be the difference between the marginal response capacity of electric vehicle users to charging station j and the marginal response capacity to other charging stations except charging station j, as shown in equation (40).

$$\begin{aligned} \frac{\partial Q(p)}{\partial p_j} &= \frac{\partial [Q_j(p_1, \cdots, p_{\mathrm{N}}) - Q_{-j}(p_1, \cdots, p_{\mathrm{N}})]}{\partial p_j} \\ &= \varphi_j - \varphi_{-j} \end{aligned} \tag{40}$$

In formula, φ_j and φ_{-j} are the marginal response capacity of EV owners to charging station j and other charging stations except charging station j respectively.

In this game, the number of electric vehicles and charging stations is limited. The selection strategy of electric vehicles and the range of charging station service fee are certain. Eqs.39-40 reflect the continuity of utility function, thus ensuring the existence of equilibrium solution of Nash game. In addition, with the consideration of EV user utility function, the strict proof of its convergence can be referred to [44].

After electric vehicle is guided by the strategy, the change of space-time distribution and charging information will have an impact on the subsequent charging service fee formulation. The order of strategies and actions has been explained in this paper, and the interaction of different subject strategies is described as follows.

Service fee is determined in the next simulation time, according to the optimal response of the charging station with the state of electric vehicles in the previous simulation moment. Therefore, the paper has actually considered the subsequent service fee adjustment strategy of charging stations during the continuous update process of electric vehicle information. In the repetition of the game, the continuous change of the state will make the strategies of both sides update constantly in stackelberg game, which reflects the interaction between the information of electric vehicles and the charging service fee formulation.

Time-sequence change of the stackelberg game result is explained as follows. We take the result of the previous moment as the input of the known quantity, and get the strategy of this moment through the game. The game results will change over time. If users make decision according to the equilibrium strategy of the game, the best game result can be obtained by using the game time sequence recurrence. However, in fact, users may not charge according to the strategy given by the game method, i.e. users are limited rational. At this time, according to the actual result, the next optimization result related to the actual result can be calculated through the game, so as to get the optimal time series pricing strategy for each charging station.

C. SOLUTION OF STATION-EVS STACKELBERG GAME MODEL

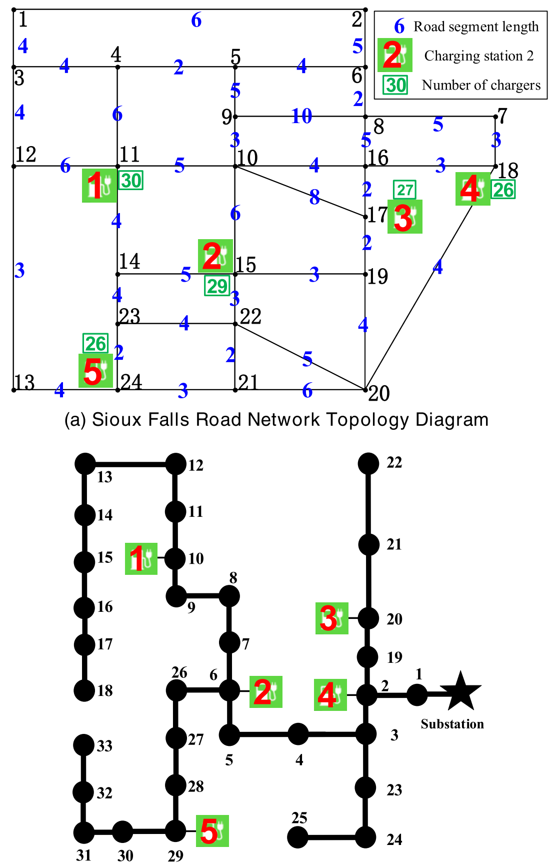
This model assumes that the service fee decision and station selection in Stackelberg game are made at the same time. Once the charging station issues the service fee, the owners of electric vehicles can quickly make a response through the payment function, and the charging stations need to constantly adjust its decision to approach the optimal solution. The algorithm steps are as follows.

Step 1, preset the service fee initial value of each charging station, which is as standard charging service fee.

Step 2, preset the order of action between charging stations, and give the maximum decision rounds N.

Step 3, in each round of decision, according to the decision of other charging stations $c_2(t), \ldots, c_n(t)$, the first charging station make its own optimal decision $c_1(t+1)$. When the decision of all charging stations is finished, $c_i(t+1)$ is used to replace the original decision, then the decision of this round is finished, and the number of rounds is increased by one.

Step 4, until all the decisions made in this round are the same as those made in the last round, or the norm of all charging stations difference between the current round and the last round is less than the given value, the operation is terminated and the convergence solution is obtained. If the maximum number of rounds is reached, the operation is terminated.



(a) Sioux Falls Road Network Topology Diagram

(b) Structure Diagram of Distribution System

FIGURE 4. Sioux Falls Diagram.

V. EXAMPLE ANALYSIS

A. INTRODUCTION OF EXAMPLES

In this paper, Sioux Falls urban road network system is used as an example. The road network topological structure and the location distribution of fast charging stations are shown in Fig.4 (a). There are 24 nodes, 76 road segments and 5 fast charging stations. The number indicated on the road segment in Fig.4 (a) represents the length of the road segment, km. Structure of Sioux Falls urban distribution network is shown in Fig.4 (b), which shows corresponding nodes for fast charging station accessing distribution network. Urban road parameters is shown in Table I.

The OD distribution of typical days in the road network is shown in Fig.5. In this paper, the more common BYD E6 is

TABLE 1. Sioux falls road parameters.

Road num	Start node	End node	Leng /km	Free flow velocity km/h	Maximum capacity 1/h	Blocking capacity 1/km
1	1	2	6	100	25900	125
2	1	3	4	100	23403	125
3	2	1	6	100	25900	125
4	2	6	5	70	4958	125
5	3	1	4	100	23403	125
6	3	4	4	70	17111	125
7	3	12	4	100	23403	125
8	4	3	4	70	17111	125
9	4	5	2	70	17783	125
10	4	11	6	70	4909	125
11	5	4	2	70	17783	125
12	5	6	4	70	4948	125
13	5	9	5	70	10000	125
14	6	2	5	70	4958	125
15	6	5	4	70	4948	125
16	6	8	2	70	4899	125
17	7	8	3	70	7842	250
18	7	18	2	70	23403	250
19	8	6	2	70	4899	250
20	8	7	3	70	7842	250
21	8	9	10	70	5050	250
22	8	16	5	70	5046	250
23	9	5	5	70	10000	250
24	9	8	10	70	5050	250
25	9	10	3	70	13916	250
26	10	9	3	70	13916	250
27	10	11	5	50	10000	250
28	10	15	6	50	13512	250
29	10	16	4	50	4855	250
30	10	17	5	50	4994	250
31	11	4	6	70	4909	250
32	11	10	5	50	10000	250
33	11	12	6	70	4909	250
34	11	14	4	70	4877	250
35	12	3	4	100	23403	250
36	12	11	6	70	4909	250
37	12	13	3	100	25900	250
38	13	12	3	100	25900	250
39	13	24	4	100	5091	250
40	14	11	4	70	4877	250
41	14	15	7	50	5128	250
42	14	23	4	70	4925	250
43	15	10	6	50	13512	250
44	15	14	7	50	5128	250
45	15	19	3	70	14565	250
46	15	22	3	70	9599	250
47	16	8	5	70	5046	250
48	16	10	4	70	4855	250
49	16	17	2	70	5230	250
50	16	18	3	70	19680	250
51	17	10	5	70	4994	250
52	17	16	2	70	5230	250
53	17	19	2	70	4824	250
54	18	7	2	70	23403	250
55	18	16	3	70	19680	250
56	18	20	4	100	23403	250
57	19	15	3	70	14565	250
58	19	17	2	70	4824	250
59	19	20	4	70	5003	250
60	20	18	4	100	23403	250
61	20	19	4	70	5003	250
62	20	21	6	100	5060	250
63	20	22	5	70	5076	250
64	21	20	6	100	5060	250
65	21	22	2	70	5230	250
66	21	24	3	100	4885	250
67	22	15	3	70	9599	250
68	22	20	5	70	5076	250
69	22	21	2	70	5230	250
70	22	23	4	70	5000	250
71	23	14	4	70	4925	250
72	23	22	4	70	5000	250
73	23	24	2	70	5079	250
74	24	13	4	100	5091	250
75	24	21	3	100	4885	250
76	24	23	2	70	5079	250

TABLE 1. *(continued)* Sioux falls road parameters.

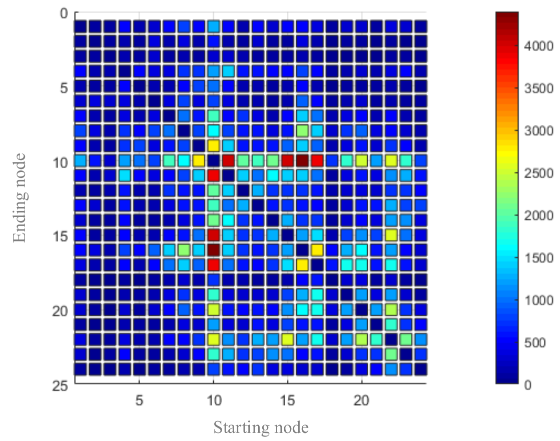


FIGURE 5. Typical daily OD distribution.

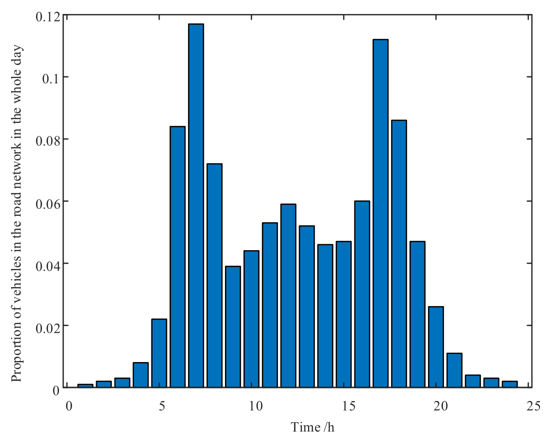
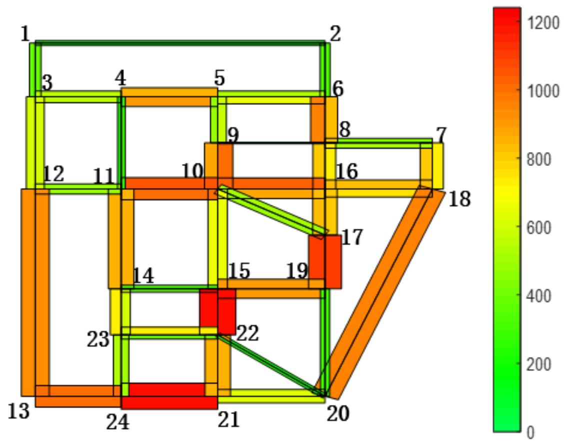
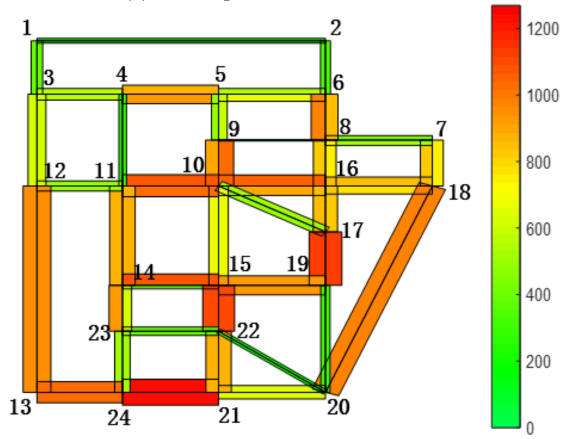


FIGURE 6. Vehicle time distribution in road network.

used for example simulation. The battery capacity is 82kWh, the endurance mileage is about 400km, and the penetration rate of electric vehicles is 10%. Considering that the charging is all fast charging scenarios, the power of the charger is set to 350kW. When EV leaves the charging station, the SOC is 90%.



(a) road Segment Flow at 7 a.m.



(b) Road Segment Flow at 8 a.m.

FIGURE 7. Road network traffic flow distribution.

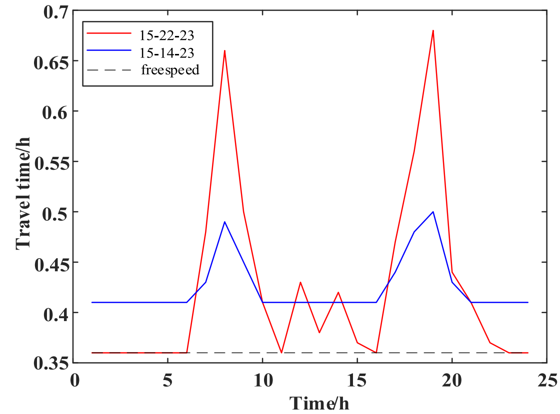


FIGURE 8. Travel time from node 15 to node 23.

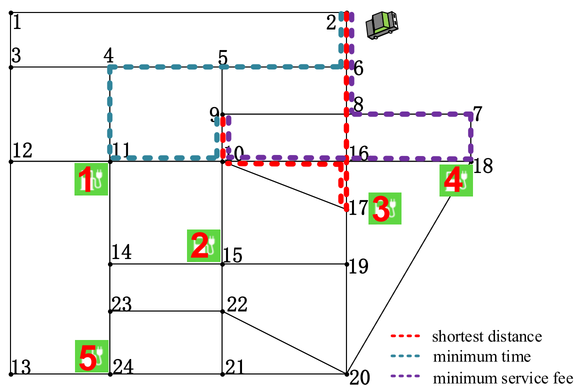


FIGURE 9. Path selection in different scenarios.

TABLE 2. Charging navigation decision information.

Num	Distance / km	Travel time / h	Queue time / h	Service fee / ¥
Scenario 1	14	0.52	0.17	1.1
Scenario 2	17	0.41	0.03	1
Scenario 3	15	0.46	0.24	0.8

B. ANALYSIS OF DYNAMIC CHARGING PATH SELECTION IN URBAN ROAD NETWORK

In this paper, the time distribution proportion of vehicles in each period of road network is obtained through OD survey, as shown in Fig.6.

Through the dynamic traffic simulation of urban road network, the traffic flow distribution at 7:00 and 8:00 am is shown in Fig.7 (a) and Fig.7 (b). In Fig.7, the larger the traffic flow is, the wider the road segment width is.

It can be seen from Fig.7 that the number of OD vehicles driving in node 15 of the road network is small in Fig.5, but it belongs to the more important hub node in the city, and the road segment between node 15 and node 22 of the road network forms the main road in the north-south direction of the city, so traffic flow of road segment 15-22 is large in the morning rush hour.

According to the analysis of the travel from node 15 to node 23 in Fig.4, there are path 1 as 15-22-23 and path 2 as 15-14-23 for selection, and the one-day travel time calculated by the dynamic travel time model is shown in Fig.8. As the total length of path 2 is 2km longer than that of path 1, considering the condition of free flow, all vehicle owners will select path 1 drive in, which results in the sharp increase of traffic flow between nodes 15 and 22 in Fig.7 (a).

It can be seen from Fig.8 that the travel time of path 1 is 0.18h longer than that of path 2 at 7 a.m. according to the optimization result of dynamic path selection model, the number of vehicles choosing path 1 at 8 a.m. is significantly reduced, and the traffic flow of path 2 increases accordingly, which plays an alternative role in easing congestion, as shown in Fig.7 (b).

Taking 7:00 a.m. as an example, this paper analyzes the charging path selection of a single EV user considering three goals: distance, time and service fee. Set the starting point of electric vehicle as node 2 and the ending point as node 9, and the decision information of charging navigation is shown in Table II.

Scenario 1 aims at the shortest distance. The distance from node 2 to charging station 3 is 14km, and the distance from

TABLE 3. Charging option at 7 a.m. considering shortest distance.

OD	Charging station	First path	Second path
9-2	3	9-10-17	17-16-8-6-2
10-23	1	10-11	11-14-23
11-14	1	11	11-14
13-10	1	13-12-11	11-10
13-22	5	13-24	24-21-22
14-9	1	14-11	11-10-9
15-9	2	15	15-10-9
17-10	3	17	17-10
19-9	3	19-17	17-10-9
23-17	2	23-22-15	15-19-17

TABLE 4. Charging option at 7 a.m. considering minimum time.

OD	Charging station	First path	Second path
7-10	4	7-18	18-16-10
15-9	2	15	15-10-9
16-22	3	16-17	17-19-15-22
20-4	4	20-18	18-7-8-6-5-4
21-9	5	21-24	24-23-14-15-10-9

TABLE 5. Charging option at 7 a.m. considering minimum service fee.

OD	Charging station	First path	Second path
8-21	4	8-7-18	18-20-21
5-19	4	5-6-8-7-18	18-20-19
16-20	4	16-18	18-20
15-7	4	15-19-20-18	18-7
10-8	4	10-16-18	18-7-8

charging station 3 to end node is 9km. The travel path is the red line shown in Fig.9.

Scenario 2 takes the minimum time as the goal, and selects charging station 1. The total consuming time before charging is 0.44h, and the travel path is the blue line shown in Fig.9.

Scenario 3 takes the minimum service fee as the goal, selects charging station 4, the service fee is 0.8¥, and the travel path is the purple line shown in Fig.9.

The path selection of other vehicles at this time is shown in Table III, Table IV, and Table V.

In this paper, the hybrid Logit model is used to solve the station selection probability of electric vehicle from each network node, as shown in Fig.10. It can be seen from Fig.10 that at the start of the travel, each charging station has a strong attraction to the electric vehicles of the nearby road network nodes.

An electric vehicle from start node 14 to end node 7 is taken as an example to analyze its station selection strategy. The electric vehicle starts from node 14 at 8:00 a.m., it passes through 3 charging stations during the driving, namely No.2, No.3 and No.4 charging station. Assume two scenarios as follows, and scenario 4 and scenario 5 both consider the charging service fee as constant.

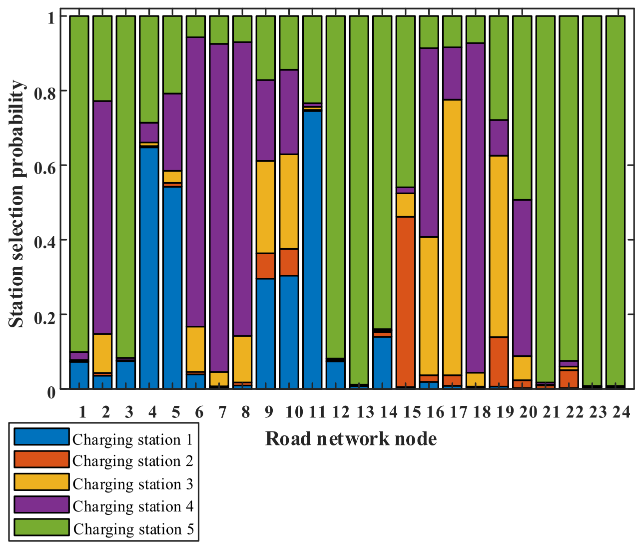


FIGURE 10. Station selection initial probability of electric vehicles.

Scenario 4 does not consider the impact of queuing time on station selection, as shown in Fig.11.

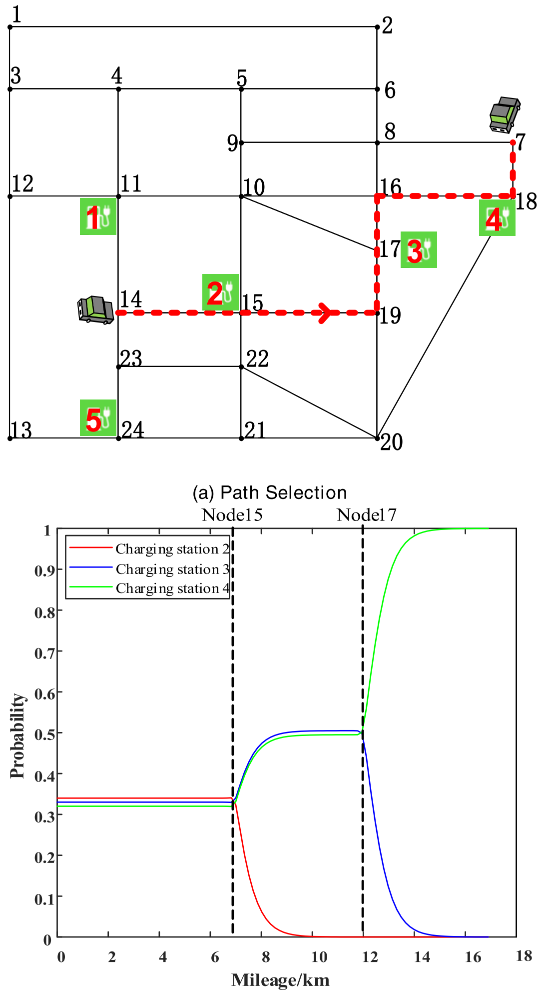
Scenario 5 considers the impact of queuing time on station selection, as shown in Fig.12.

It can be seen from Fig.11 that before arriving at charging station 2, the owner has no clear tendency to charge at which of charging stations. But after passing through charging station 2, there are still two charging stations to be selected ahead of the path, and it will not turn back to charging station 2. Therefore, the selection probability of charging station 2 drops rapidly to 0.

It can be seen from Fig.12 that there are many charging vehicles in charging station 3 at the initial time, and the queuing time is long. Therefore, the selection probability of charging station 3 is the lowest before the electric vehicle passes node 15. After passing node 15, although the queuing time of charging station 2 is not the longest, the selection probability of charging station 2 is greatly reduced because it is located in the opposite direction of vehicle driving.

Under the condition of dynamic change of service fee, an electric vehicle from start node 16 and end node 23 is selected to compare the influence of service fee change on its station selection strategy. The initial service fee of five charging stations is 1¥ /kWh. When the vehicle owner drives to node 17, the service fee is adjusted. After adjusting, the service fee is 1.3 ¥ /kWh, 1.5 ¥ /kWh, 1.2 ¥ /kWh, 1 ¥ /kWh and 1 ¥ /kWh respectively. The station selection probability considering service fee adjustment is shown in Fig.13.

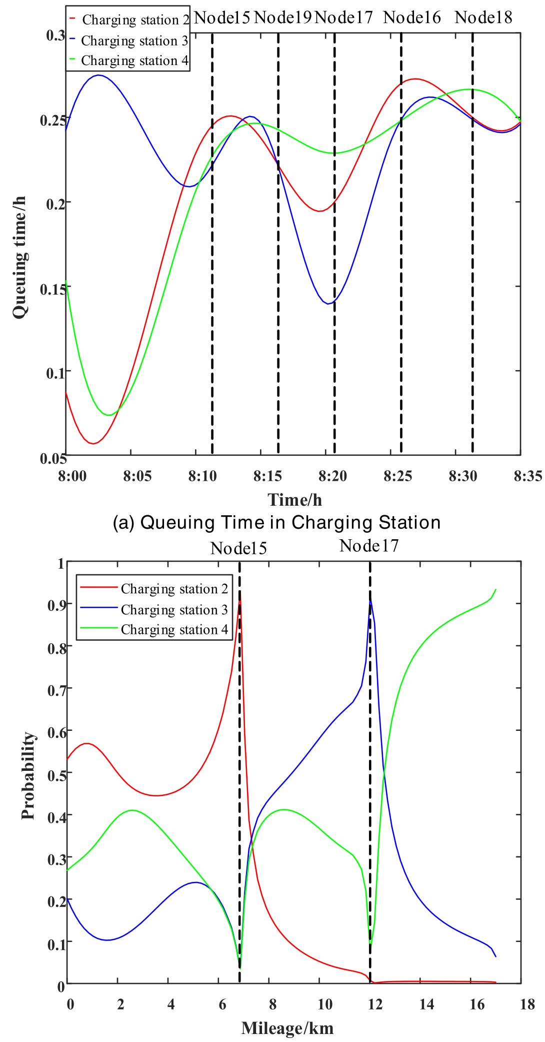
The original path of the car owner, which is the dotted line shown in Fig.13, via charging station 2 before the service fee unadjusted. The selection probability of charging station 5, which is not on the original path, is low. The service fee is updated after node 17, the electric vehicle is still moving towards the direction close to charging stations 2 and 5, and the selection probability of both increases. When driving to



(a) Path Selection

(b) Charging Station Selection Probability

FIGURE 11. **Dynamic station selection probability of electric vehicle.**



(a) Queuing Time in Charging Station

(b) Charging Station Selection Probability

FIGURE 12. **Dynamic station selection probability considering queuing time.**

node 20 after node 19, the value of payment function of charging station 5 increases rapidly, so its selection probability also increases, which reflects the advantages of dynamic charging navigation.

C. ANALYSIS OF MULTI-AGENT STACKELBERG GAME

The optimization results of queuing time are shown in Fig.14. With the increase of fast charging vehicles, the queuing time of charging station 3,which is affected by the disordered charging of electric vehicles at 8:15 a.m., has exceeded 0.4h. It indicates that the charging demand of electric vehicles at charging station 3 exceeds its service capacity. While charging vehicles at charging station 4 do not need to queue, the variance of queuing time between five charging stations reaches 0.187 at this time. It can be seen from Fig.14 that the charging vehicles at the following time are reasonably guided, part of the charging vehicles are transferred to charging station 4, and the queuing time of charging station 3 is also reduced. At 10:00 a.m., the variance between 5 charging

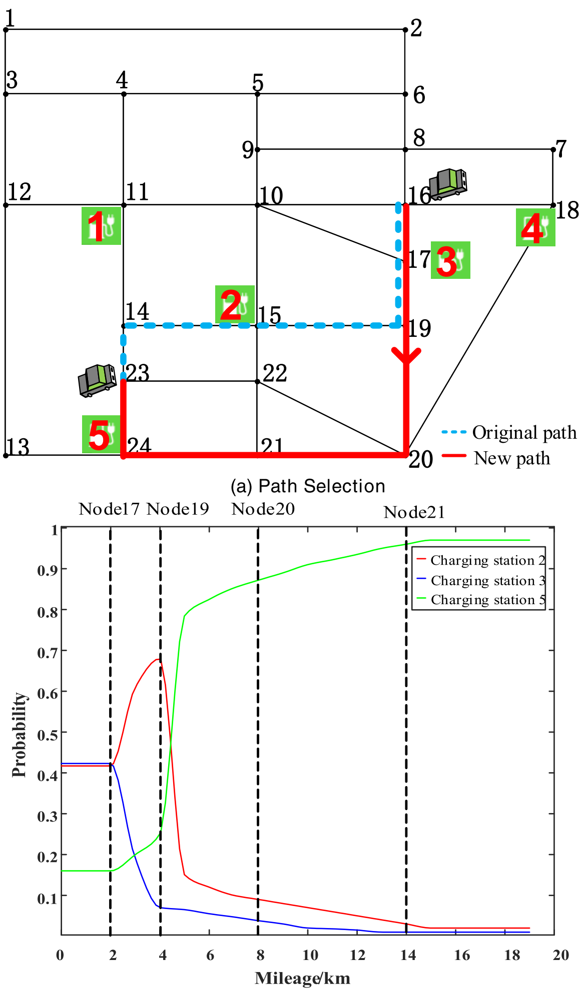
TABLE 6. **Charging station operation information.**

Charging Station	1	2	3	4	5
Queuing Time / h	0.076	0.208	0.15	0.229	0.034
Land rent (¥ / m^2·day)	125	182	102	79	61

stations is only 0.026. The service capacity of each station has been fully utilized.

Considering the pricing game between charging stations, the pricing scheme between charging stations is obtained by the model solution method in Section B of Part IV, as shown in Fig.15. The maximum number of rounds is set to 150. The example parameters are shown in Table VI.

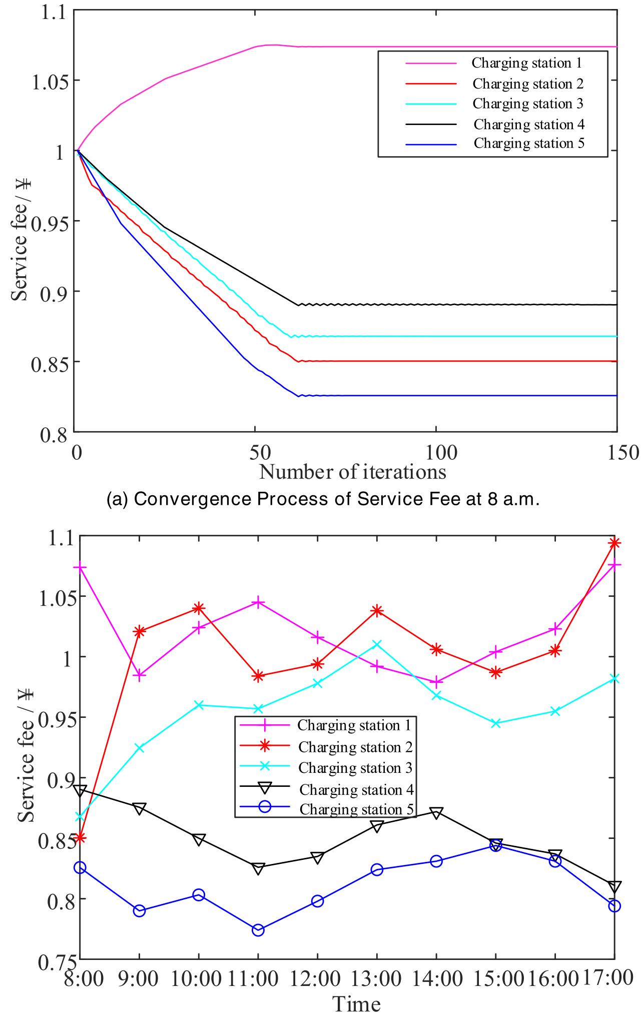
It can be seen from Fig.15 that the game converges in about 60 generations. Charging station 1 and 2 are located close to the center of the road network, and a large number of electric vehicles have the willingness to charge. Therefore, charging station 1 and 2 have the high service fee to maximize their own benefits. The location of charging station 3 is moderate.



(a) Path Selection

(b) Charging Station Selection Probability

FIGURE 13. **Station selection probability considering service fee adjustment.**



(a) Convergence Process of Service Fee at 8 a.m.

(b) Service fee-time Curve

FIGURE 15. **Pricing game between charging stations.**

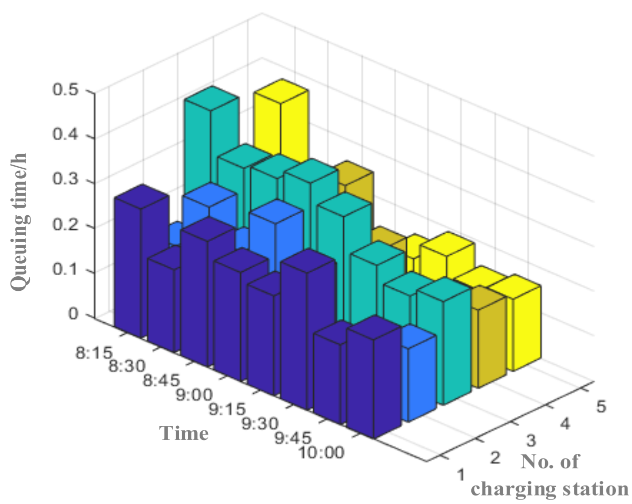
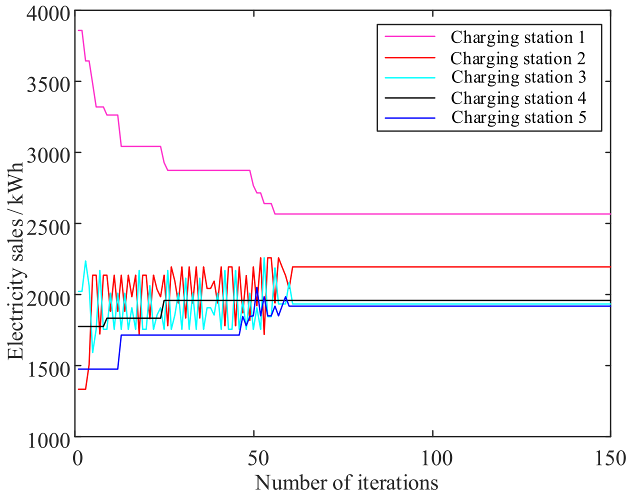


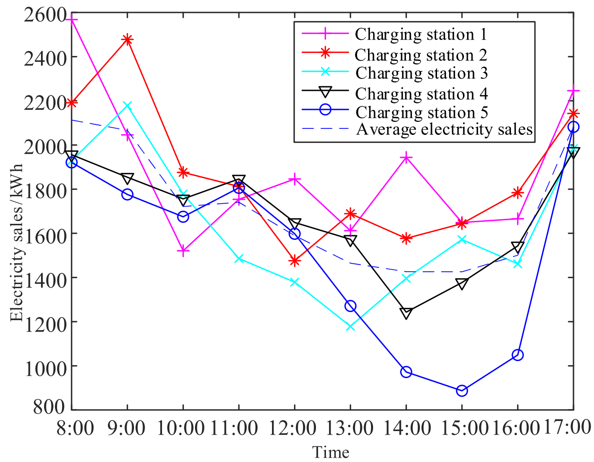
FIGURE 14. **Evolution of queuing time.**

The charging demand of electric vehicles at charging station 3 is less than its service capacity limit, so its service fee is slightly lower than that of station 1 and 2. Charging station 4 and 5 are located in a remote place, so there are few charging vehicles at stations. Therefore, it is necessary to attract electric vehicles to charge at a low price to maximize the revenue and realize the spatial transfer of fast charging load.

The electricity sales result of charging stations is shown in Fig.16. Electricity sales of charging station 1 and 2 is large from the whole period, which exceeds the average electricity sales at most of time. The above two stations are located near the traffic hub, which reflects their strong ability to attract charging demand. 3 p.m. is the low point of fast charging demand, and the electricity sales of all stations are at the lowest point in the daytime. It can be seen from Fig.16 that the electricity sales of each station is equalized and at a high level in morning peak and evening peak hours, which shows that through the adjustment of service fee, the charging demand of charging station 1 and 2 is partially transferred to charging station 4 and 5, effectively reducing the load of distribution lines around charging station 1 and 2, and realizing peak cutting and valley filling.



(a) Convergence Process of Electricity Sales at 8 a.m.



(b) Electricity sales-time Curve

FIGURE 16. Charging station electricity sales game.

In terms of distribution network node voltage, the average maximum voltage deviation rate of the distribution network access node for charging station 1 is 9.65% before adjusting the service fee. The average maximum voltage deviation rate decreases to 9.13% after adjusting the service fee. The average maximum voltage deviation rate of the distribution network access node for charging station 5 is 6.23% before adjusting the service fee. The average maximum voltage deviation rate decreases to 6.41% after adjusting the service fee. The results show that the reasonable distribution of electric vehicle charging load can improve the voltage level of distribution network after the dynamic service fee adopted, and the operation of distribution network will be safer and more reliable, which supports the theoretical description in Section B of Part IV.

VI. CONCLUSION

In this paper, a dynamic response strategy of fast charging station-EVs considering interaction of multiple vehicles is proposed. In the study of EV charging navigation scheme selection, this paper pays attention to modeling from the perspective of EVs, which can reflect the interactive influence of charging station selection among a large number of electric vehicles and satisfy different response characteristics of the electric vehicle users. In the research of station-EVs interaction, the charging service fee considers the control of users' charging behavior and the influence of price game between multiple stations on equalizing the load of charging stations.

The dynamic response strategy is evaluated on a real data of the Sioux Falls urban road network system. Conclusions are made below from the perspective of dynamic charging path selection and dynamic charging service fee decision based on multi-agent stackelberg game.

(1) The performance of the proposed dynamic response strategy in terms of dynamic charging path selection

Based on the case study results, the charging path can be optimized by applying the dynamic response strategy.

a) Avoiding road congestion

As the total length of path 2 is 2km longer than that of path 1, considering the condition of free flow, all vehicle owners will select path 1 drive in. But the travel time of path 1 is 0.18h longer than that of path 2 at 7 a.m. according to the optimization result of dynamic path selection model, the number of EVs choosing path 1 at 8 a.m. is significantly reduced, and the traffic flow of path 2 increases accordingly. The proposed dynamic response strategy plays an important role in avoiding road congestion.

b) Proposing differentiated charging navigation schemes

Taking 7:00 a.m. as an example, this paper analyzes the charging path selection of a single EV user considering three goals as follows. Scenario 1 aims at the shortest distance, the distance, travel and queue time, service fee were 14km, 0.69h, 1.1¥ respectively. Scenario 2 aims at the minimum time, the distance, travel and queue time, service fee were 17km, 0.44h, 1¥ respectively. Scenario 3 aims at the minimum service fee, the distance, travel and queue time, service fee were 15km, 0.7h, 0.8¥ respectively.

The proposed dynamic response strategy can guide the fast charging load to move orderly in the road network according to the different response characteristics of the electric vehicle users.

c) Charging station selection probability varies with service fee

After passing through a charging station, there are still charging stations to be selected ahead of the path, and EV will not turn back to this charging station. Therefore, the selection probability of charging station reduced greatly, which is located in the opposite direction of vehicle driving. The selection probability of charging stations to be selected increased, which is located in the ahead of the vehicle driving path.

With the value of payment function (21) increases, selection probability of charging stations to be selected ahead of the path also increases, which reflects the advantages of the proposed dynamic response strategy.

(2) The performance of the proposed dynamic response strategy in terms of dynamic charging service fee decision

Class I charging stations are located close to the center of the road network, which can increase service fee to maximize their own benefits. Class II charging stations are located in a remote place of the road network, which should reduce service to attract EVs charging and maximize the revenue. The proposed dynamic response strategy realizes the spatial transfer of fast charging load, effectively reduce the load of distribution lines around charging stations, and realize peak cutting and valley filling.

In terms of distribution network node voltage, the average maximum voltage deviation rate of the distribution network access node for the class I charging station is from 9.65% to 9.13%, after increasing the service fee. The average maximum voltage deviation rate of the distribution network access node for the class II charging station is from 6.23% to 6.41%, after reducing the service fee.

The results show that the reasonable distribution of electric vehicle charging load can improve the voltage level of distribution network after the dynamic service fee adopted, and the operation of distribution network will be safer and more reliable.

In general, the proposed dynamic response strategy considers the interests of the charging station and the owner, guides the fast charging load to move orderly in the road network according to the different response characteristics of the electric vehicle users, equalizes the charging demand between different fast charging stations and effectively reduce the peak load of distribution lines around charging stations.

In this paper, when analyzing the pricing game of charging stations, it is assumed that different stations belong to different operators and there is a competitive relationship between them. With the development of the fast charging station, a few strong operators may occupy most of the market share in the future. Therefore, the research on the pricing strategy of the operator consortium will be a key point in the future. The fast charging station in the city center will no longer be able to meet the increasing charging demand due to the factors such as land price and the load rate of the power grid. The urban fast charging station planning is also a research direction in the future based on the load spatial transfer characteristics of EVs.

REFERENCES

[1] *A Study on China's Timetable for Phasing-Out Traditional Ice-Vehicles*, Innov. Energy Transp. Center, Los Angeles, CA, USA, May 2019.

[2] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Trans. Transp. Electrific.*, vol. 4, no. 1, pp. 76–88, Mar. 2018.

[3] R. Mehta, D. Srinivasan, A. M. Khambadkone, J. Yang, and A. Trivedi, "Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure," *IEEE Trans. Smart Grid*, vol. 9, no. 1, pp. 299–312, Jan. 2018.

[4] W. Mo, C. Yang, X. Chen, K. Lin, and S. Duan, "Optimal charging navigation strategy design for rapid charging electric vehicles," *Energies*, vol. 12, no. 6, p. 962, Mar. 2019.

[5] D. Zhaohao, L. Ying, and Z. Lizi, "A stochastic resource planning scheme for PHEV charging station considering energy portfolio optimization and price-responsive demand," *IEEE Trans. Ind. Appl.*, vol. 54, no. 6, pp. 5590–5598, Nov./Dec. 2018.

[6] J. Tan and L. Wang, "Real-time charging navigation of electric vehicles to fast charging stations: A hierarchical game approach," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 846–856, Mar. 2017.

[7] M. H. Amini, J. Mohammadi, and S. Kar, "Distributed holistic framework for smart city infrastructures: Tale of interdependent electrified transportation network and power grid," *IEEE Access*, vol. 7, pp. 157535–157554, 2019.

[8] Z. Qian, W. Zhong, and T. Weiyu, "Spatial-temporal distribution prediction of charging load of electric vehicle based on MDP random path simulation," (in Chinese), *Automat. Electr. Power Syst.*, vol. 42, no. 20, pp. 65–72, 2018.

[9] F. J. Soares, J. A. P. Lopes, and P. M. R. Almeida, "A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid," in *Proc. 17th Power Syst. Comput. Conf.*, Stockholm, Sweden, 2011, pp. 1–7.

[10] S. Shu, L. Xiangning, and Z. Hongzhi, "Spatial and temporal distribution model of electric vehicle charging demand," (in Chinese), *Proc. CSEE*, vol. 37, no. 16, pp. 54–65 and 322, 2017.

[11] A. I. Adamatzky, "Computation of shortest path in cellular automata," *Math. Comput. Model.*, vol. 23, no. 4, pp. 105–113, Feb. 1996.

[12] M. Batty, *Cities and Complexity: Understanding Cities With Cellular Automata, a Gent-Based Models and Fractals*, 1st ed. Cambridge, MA, USA: MIT Press, 2007.

[13] J. G. Hayes and K. Davis, "Simplified electric vehicle powertrain model for range and energy consumption based on EPA coast-down parameters and test validation by Argonne national lab data on the Nissan leaf," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Dearborn, MI, USA, Jun. 2014, pp. 1–6.

[14] S. Sun, Q. Yang, and W. Yan, "Optimal temporal-spatial electric vehicle charging demand scheduling considering transportation-power grid couplings," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Portland, OR, USA, Aug. 2018, pp. 1–5.

[15] Y. Hongming, L. Ming, and W. Fushuan, "Route selection and charging navigation strategy for electric vehicle employing real-time traffic information perception," (in Chinese), *Automat. Electr. Power Syst.*, vol. 41, no. 11, pp. 106–113, 2017.

[16] T. Jurik, A. Cela, R. Hamouche, R. Natowicz, A. Reama, S.-I. Niculescu, and J. Julien, "Energy optimal real-time navigation system," *IEEE Intell. Transp. Syst. Mag.*, vol. 6, no. 3, pp. 66–79, Jul. 2014.

[17] Q. Guo, S. Xin, H. Sun, Z. Li, and B. Zhang, "Rapid-charging navigation of electric vehicles based on real-time power systems and traffic data," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1969–1979, Jul. 2014.

[18] H. Hui, F. Hao, and S. Shu, "Multilateral win-win strategy for smart charging service of electric vehicle," (in Chinese), *Automat. Electr. Power Syst.*, vol. 41, no. 19, pp. 66–73, 2017.

[19] D. Wu, D. C. Aliprantis, and L. Ying, "Load scheduling and dispatch for aggregators of plug-in electric vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 368–376, Mar. 2012.

[20] J. Hu, S. You, M. Lind, and J. Ostergaard, "Coordinated charging of electric vehicles for congestion prevention in the distribution grid," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 703–711, Mar. 2014.

[21] L. Hong, Z. Xu, and L. Chang, "Timing interactive analysis of electric private vehicle traveling and charging demand considering the sufficiency of charging facilities," (in Chinese), *Proc. CSEE*, vol. 38, no. 18, pp. 5469–5478, 2018.

[22] S. Bae and A. Kwasinski, "Spatial and temporal model of electric vehicle charging demand," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 394–403, Mar. 2012.

[23] M. D. Galus, R. A. Waraich, F. Noembrini, K. Steurs, G. Georges, K. Boulouchos, K. W. Axhausen, and G. Andersson, "Integrating power systems, transport systems and vehicle technology for electric mobility impact assessment and efficient control," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 934–949, Jun. 2012.

[24] J.-Y. Yang, L.-D. Chou, and Y.-J. Chang, "Electric-vehicle navigation system based on power consumption," *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 5930–5943, Aug. 2016.

[25] H. Yang, Y. Deng, J. Qiu, M. Li, M. Lai, and Z. Y. Dong, "Electric vehicle route selection and charging navigation strategy based on crowd sensing," *IEEE Trans Ind. Informat.*, vol. 13, no. 5, pp. 2214–2226, Oct. 2017.

[26] X. Dong, Y. Mu, X. Xu, H. Jia, J. Wu, X. Yu, and Y. Qi, "A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks," *Appl. Energy*, vol. 225, pp. 857–868, Sep. 2018.

[27] I. S. Bayram, G. Michailidis, and M. Devetsikiotis, "Unsplittable load balancing in a network of charging stations under QoS guarantees," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1292–1302, May 2015.

[28] J. Johnson, M. Chowdhury, Y. He, and J. Taiber, "Utilizing real-time information transferring potentials to vehicles to improve the fast-charging process in electric vehicles," *Transp. Res. C, Emerg. Technol.*, vol. 26, pp. 352–366, Jan. 2013.

[29] P. C. Fishburn and A. M. Odlyzko, "Dynamic behavior of differential pricing and quality of service options for the Internet," *Decis. Support Syst.*, vol. 28, nos. 1–2, pp. 123–136, Mar. 2000.

[30] S. Yingchi, M. Yunfei, and L. Jiaying, "A fast charging guidance strategy for multiple demands of electric vehicle, fast charging station and distribution network," (in Chinese), *Automat. Electr. Power Syst.*, to be published.

[31] C. Lixing and H. Xueliang, "Ordered charging strategy of electric vehicles at charging station on highway," (in Chinese), *Electr. Power Autom. Equip.*, vol. 39, no. 1, pp. 112–117 and 126, 2019.

[32] G. Gangjun, L. Anqin, and C. Zhimin, "Cyber physical system of active distribution network based on edge computing," *Power Syst. Technol.*, vol. 42, no. 10, pp. 3128–3135, 2018.

[33] Y. Mu, J. Wu, N. Jenkins, H. Jia, and C. Wang, "A spatial–temporal model for grid impact analysis of plug-in electric vehicles," *Appl. Energy*, vol. 114, pp. 456–465, Feb. 2014.

[34] G. Shaoyun, Z. Linwei, and L. Hong, "Optimal deployment of electric vehicle charging stations on the highway based on dynamic traffic simulation," (in Chinese), *Trans. China Electrontech. Soc.*, vol. 33, no. 13, pp. 91–101, 2018.

[35] M. B. Arias, M. Kim, and S. Bae, "Prediction of electric vehicle charging-power demand in realistic urban traffic networks," *Appl. Energy*, vol. 195, pp. 738–753, Jun. 2017.

[36] S. Opricovic and G.-H. Tzeng, "Extended VIKOR method in comparison with outranking methods," *Eur. J. Oper. Res.*, vol. 178, no. 2, pp. 514–529, Apr. 2007.

[37] I. Yperman, *The Link Transmission Model for Dynamic Network Loading*. Leuven, Belgium: Katholieke Univ., 2007.

[38] D. Liu, T. Qi, K. Zhang, and Y. Guo, "Beijing residents' travel time survey in small samples," *J. Transp. Syst. Eng. Inf. Technol.*, vol. 9, no. 2, pp. 23–26, Apr. 2009.

[39] A. S. Masoum, S. Deilami, P. S. Moses, M. A. S. Masoum, and A. Abu-Siada, "Smart load management of plug-in electric vehicles in distribution and residential networks with charging stations for peak shaving and loss minimisation considering voltage regulation," *IET Gener., Transmiss. Distrib.*, vol. 5, no. 8, pp. 877–888, 2011.

[40] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp. 456–467, Sep. 2011.

[41] P. Bangalore, "Development of test system for distribution system reliability analysis, integration of electric vehicles into the distribution system," Ph.D. dissertation, Dept. Energy Environ., Division Electr. Power Eng., Chalmers Univ. Technol., Gothenburg, Sweden, 2011.

[42] S. Shu, S. Jinwen, L. Xiangning, and L. Xianshan, "Electric vehicle smart charging navigation," *Proc. CSEE*, vol. 33, no. S1, pp. 59–67, 2013.

[43] *Notice on Matters Related to Electricity Price Policy for Electric Vehicles*, China Develop. Reform Commission, Beijing, China, Jul. 2014.

[44] D. Xicai and G. Huahua, "Existence of the equilibrium solution of a two—Stage leaders-followers gamee," *Math. Econ.*, vol. 26, no. 4, pp. 50–53, 2009.

XIAOOU LIU received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tianjin University, in 2007, 2010, and 2019, respectively.

He is currently a Senior Engineer with the China Energy Engineering Group Tianjin Electric Power Design Institute Corporation, Ltd. He has contributed to a number of research projects granted from the National Natural Science Foundation of China and industry corporations. He has published more than six peer-reviewed academic articles and holds more than two invention patents of China. His research interests include simulation, analysis, operation and planning in smart distribution systems, integrated energy systems, and electric vehicles.