A Planning Method for Highways Charging piles Based on Dynamic Traffic Simulation

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ABSTRACT

With the significant improvement of the national economic level, China's automobile ownership continues to rise. A complete station(pile) is an important guarantee for the popularization of vehicles. Reasonable planning of charging piles is crucial for promoting vehicles. As a means of transportation, vehicles have both road network load attributes and distribution network load attributes. Vehicles fulfill users' travel needs in the road network and obtain energy supply in the distribution network. They are a key link between the transportation and distribution systems, and an important component of the energy internet. This article first proposes a method based on dynamic traffic simulation to obtain the arrival rate of charging piles, and then calculates the time of waiting of vehicles. Then, taking the time of waiting for electric vehicle charging and the minimum cost of charging pile construction and operation as the goals of two stakeholders, a multi-objective planning model for highway electric vehicle charging piles is established. Once again, the multi-objective particle swarm optimization algorithm is used to solve the model and obtain Pareto frontiers. VIKOR is used to sort the frontiers and select the optimal solution. Finally, the rationality of the method is verified through numerical examples.

Keywords: electric vehicles, charging pile planning, highways, distribution networks, waiting time, multi-objective planning, swarm optimization algorithm, transportation

1. INTRODUCTION

With the continuous improvement of China's economic and social development level, the number of cars, as an important means of transportation, continues to increase. Vigorously promoting the development of vehicles in the electric vehicle industry can promote energy conservation and emission reduction, prevent and control air pollution, accelerate fuel substitution. As the foundation for the development of vehicles, the construction of global charging facilities has also achieved rapid growth.

At present, in terms of planning research methods, there are mainly two methods: dividing by functional areas and dividing by service scope. Ref [1] considers the correlation of travel variables in travel chain simulation and establishes their probability distribution models. According to the method of dividing the service scope, the urban area is usually divided into several service areas using weighted V-maps, P-center positioning models, etc. According to certain division principles, each charging pile serves the charging needs of vehicles within a certain area. Ref [2] uses weighted Voronoid diagrams to divide urban areas into different service areas, and adjusts the weights based on the spatial distribution of electric vehicle density to calculate the charging load of different areas, and then conducts charging pile location and capacity determination. Reference [3] considers the mutual influence between different charging facilities and obtains planning solutions for various charging facilities based on an improved P-center positioning model. The driving and charging behaviors of vehicles with different uses vary greatly, so different considerations are needed. Reference [4] considers that taxis consider both the overall time consumption and the convenience of finding passengers when choosing charging piles. Based on a utility model, a probability selection function for taxis to charge stations is established, and an optimization planning model for electric taxi charging piles is proposed. Reference [5] proposed a random probability behavior model for taxis, considering the reliability of road travel time, and established a multi-objective planning model for electric taxi charging piles. There are significant differences in structure, traffic density, and other aspects between urban road networks and intercity road networks, resulting in differences in planning methods. Most research on charging facility planning is mainly focused on urban areas, and some literature has conducted

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planning for charging piles on intercity highway networks. Reference [6] analyzed the probability of vehicles charging when passing through charging piles based on electricity distribution and driving distance. A location model was established with the goal of maximizing the expected number of vehicles entering highway charging piles, and a fixed capacity model for charging piles was established through queuing theory. Reference [7] analyzed the distribution of charging demand for vehicles in the high-speed road network and established a two-stage model for optimizing the layout of electric vehicle charging piles in the high-speed road network. Reference [8] proposed a simulation method for dynamic traffic flow on highways and established an optimization planning model for highway charging piles. However, it was unable to consider the mutual influence between various sections in the two-dimensional road network, and the application of the model has certain limitations.

The existing planning methods for electric vehicle charging facilities can effectively consider the charging load during the stopping process of vehicles, but there is still a lack of a scientific and reasonable method to analyze user driving behavior during the driving process, and establish a method that can accurately analyze the spatiotemporal distribution of charging load during the driving process of vehicles in the road network. In addition, most studies are applicable to the planning of charging piles in urban areas, and there is relatively little research on the planning methods of charging piles in the high-speed road network.

2. TRAFFIC FLOW SIMULATION METHOD

The transportation system and power system are important components of the energy internet. As a means of transportation, vehicles meet travel needs while driving in the transportation system, and are charged in the power system to obtain energy supply. They are an important link between the transportation system and the power system. Therefore, simulating the driving characteristics of large-scale vehicles in the road network is crucial for analyzing the spatiotemporal characteristics of charging loads during electric vehicle driving, and is of great significance for planning urban and intercity fast charging piles. This article mainly introduces the dynamic simulation about traffic method based on the linking transmission model. This model was divided into road segment model and node model, and based on this model, the location of traffic situation at different locations and times in a road network can be dynamically simulated.

2.1 LTM road segment model

The road transmission model uses the Cumulative Vehicle Number (CVN) $N(x,t)$ (cumulative number of vehicles passing through a certain observation point) describing the propagation of traffic flow on the road net, where x and t represent the spatial location and time on the road net, respectively. Taking part differentiation of CVN yields the flowing function $q(x,t)$ and dens function $p(x,t)$.

$$\begin{cases} q(x,t) = \dfrac{\partial N(x,t)}{\partial t} \\ p(x,t) = -\dfrac{\partial N(x,t)}{\partial x} \end{cases} \tag{1}$$

In addition, the second-order partial differential of $N(x,t)$ is equal, i.e

$$\frac{\delta^2 N(x,t)}{\delta t \delta x} = \frac{\delta^2 N(x,t)}{\delta x \delta t} \tag{2}$$

Substituting equation (1) into equation (2) yields the LWR conservation equation

$$\frac{\delta q(x,t)}{\delta x} + \frac{\delta p(x,t)}{\delta t} = 0 \tag{3}$$

The road section transmission model LTM adopts a fundamental diagram (FD) of triangles, as shown in Figure 1. This basic diagram can be described in terms of free flow velocity (v_f), congestion density (p_{jam}), and maximum capacity (q_{max}). Through these three parameters, the critical density (p_{crit}) and shock wave backward propagation velocity (w) can be calculated. The LTM road segment model is used to calculating the receiving and sending ability of the road segment.

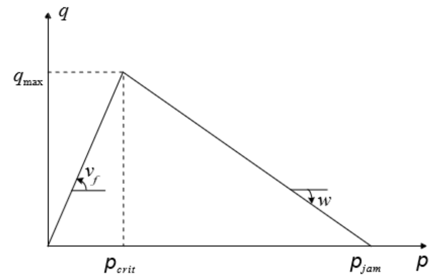

Figure 1. Triangle basic diagram

The transmission capacity of section a is represented by the time period $[t, t+\Delta t]$. The maximum quantity of vehicles that woll flow downstream of section a, denoted by $S_a(t)$. It is constrained by the upstream entrance traffic flow and downstream exit flow capacity of the section, and the calculation formula is as follows:

$$S_a(t) = \min\left\{N\left(x_a^0, t+\Delta t - L_a / v_a\right) - N\left(x_a^1, t\right), q_a^1(t)\Delta t\right\} \tag{4}$$

In the equation, x_a^0、x_a^{L}、L_a、v_a、$q_a^1(t)$ represent the upstream position, downstream position, length, flow, and flow capacity of section a.

The reception capacity of section a is represented by the maximum number of vehicles that can flow into the road section at the time period $[t, t+\Delta t]$, denoted by $R_a(t)$. It is constrained by the downstream exit traffic flow and the upstream inlet inflow capacity of the section, and the calculation formula is as follows:

$$R_a(t) = \min\left\{N\left(x_a^{\mathrm{L}}, t+\Delta t + L_a / w_a\right) + L_a p_{jam} - N\left(x_a^0, t\right), q_a^0(t)\Delta t\right\} \tag{5}$$

In the equation, w_a and $q^0{}_a(t)$ respectively represent the transitory wave back propagating velocity and upstream inflow capacity of section a.

2.2 LTM node model

In the transportation network $G(N, A)$ represented by graph theory, N is the set of nodes; A is the set of edges; For node n ($n \in N$), use A_n to represent the set of road segments entering node n; Use B_n to represent the set of road segments leaving node n. The LTM is used to calculate time period $[t, t+\Delta t]$. Traffic flow from section a to b, $G_{ab}(t)$, is constrained by the sending capacity $S_a(t)$ of section a and the receiving capacity $R_b(t)$ of section b. It is possible to calculate the diversion $S_{ab}(t)$ of the sending capacity $S_a(t)$ of section a:

$$S_a(t) \sum_{b=B_n} S_{ab}(t) \tag{6}$$

$$S_{ab}(t) = \sum_{pep} \delta_{bp}\left[N_p\left(x_a^0, t_{x_a}\left(N\left(x_a^{\mathrm{L}}, t\right) + S_a(t)\right)\right) - N_p\left(x_a^{\mathrm{L}}, t\right)\right] \tag{7}$$

In the formula: $S_{ab}(t)$ is the flow sent from section a to section b; p is the path; δ_{bp} is the correlation matrix between road segments and paths δ If segment b is on path p, then δ_{bp} =1, otherwise δ_{bp} =0; $t_{x_a}\left(N\left(x_a^{\mathrm{L}}, t\right) + S_a(t)\right)$ represents the moment when the $N\left(x_a^{\mathrm{L}}, t\right) + S_a(t)$ vehicle passes through the upstream entrance boundary of section a at point x_a^0.

$R_{ab}(t)$ represents the traffic flow allocated from section b to section a, while $p_{ab}(t)$ represents the priority coefficient for the traffic flow from section a to enter section b, satisfying $\sum_{a \in A_n} p_{ab}(t) = 1$. Therefore, the diversion $R_{ab}(t)$ of the receiving capacity $R_b(t)$ of section b can be calculated

$$R_{ab}(t) = p_{ab}(t) R_b(t) \tag{8}$$

Assuming that the propagation of traffic flow on a road segment meets FIFO principle.

$$G_{ab}\left(t\right)=\min\left(S_a\left(t\right),R_b\left(t\right)\right) \tag{9}$$

$$G_{ab}(t)=\min_{b\in B_n}\{R_{ab'}(t)/S_{ab'}(t),1\}\cdot S_{ab}(t) \tag{10}$$

$$G_{ab}(t)=\min\left(S_{ab}(t),p_{ab}(t)R_b\right) \tag{11}$$

$$G_b(t)=\min\left(N_r\left(t+\Delta t\right)-N\left(x_b^0,t\right),R_b\left(t\right)\right) \tag{12}$$

$$G_a(t)=S_a(t) \tag{13}$$

2.3 CVN update method

By using node models and link models, the cumulative inflow and outflow of the road segment can be updated

$$N(x_a^{\mathrm{L}},t+\Delta t)=N(x_a^{\mathrm{L}},t)+\sum_{b\in B_n}G_{ab}\left(t\right) \tag{14}$$

$$N(x_b^0,t+\Delta t)=N(x_b^0,t)+\sum_{a\in A_l}G_{ab}(t) \tag{15}$$

By using node models and link models, the cumulative inflow and outflow of the road segment can be updated

$$N^p\left(x_a^{\mathrm{L}},t+\Delta t\right)=N^p\left(x_a^0,t_{x_a^0}\left(N\left(x_a^{\mathrm{L}},t+\Delta t\right)\right)\right) \tag{16}$$

$$N^p\left(x_b^0,t+\Delta t\right)=N^p\left(x_b^0,t\right)+\sum_{a\in A_n}\delta_{bp}G_{ab}\left(t\right) \tag{17}$$

2.4 Calculation of traffic density

Consider any point in the road network space, assuming x is on section a, i.e. $x_a^0<x<x_a^L$. The transmission capacity $S(x,t)$ and reception capacity $S(x,t)$ at this point as follows

$$S\left(x,t\right)=|\min\left\{N\left(x_i^0,t+\Delta t-\frac{x-x_a^0}{v}\right)-N\left(x,t\right),q_a^x\left(t\right)\Delta t\right\} \tag{18}$$

$$R\left(x,t\right)=\min\left\{N\left(x_i^{\mathrm{L}},t+\Delta t+\frac{x_a^L-x}{w}\right)+p_{jam}\left(x_a^{\mathrm{L}}-x\right)-N\left(x,t\right),q_a^x\left(t\right)\Delta t\right\} \tag{19}$$

$$N\left(x,t\right)=\min\left(N\left(x_i^0,t-\frac{x-x_a^0}{V}\right),N\left(x_i^{\mathrm{L}},t+\frac{x_a^L-x}{w}\right)+p_{jam}\left(x_a^{\mathrm{L}}-x\right)\right) \tag{20}$$

According to equations (11), the traffic flow at any position and time on the road section can be calculated:

$$q\left(x,t\right)=\lim_{\Delta t\to 0}\frac{N\left(x+\Delta x,t\right)-N\left(x,t\right)}{\Delta t} \tag{21}$$

2.5 M/M/C queuing model

Vehicles arriving at charging piles to receive services are mutually independent, satisfying smoothness, independence, and commonality. Therefore, the Poisson process can be used to describe the law of vehicles arriving at charging piles. This article assumes that:

(1) λ The Poisson process, where λ satisfy

$$\lambda=k_{psn}a_{ar}q(x_i,t) \tag{22}$$

In the formula: k_{pen} is the rate of vehicles, α_{arr} is the entry rate of vehicles at the highway charging pile, which can be predicted.

(2) There are a total of c homogeneous chargers in the high-speed charging pile, each with a relatively independent service time and following the parameters of μ Negative exponential distribution .

$$\mu = k \frac{P_{ar}}{SOC_{ar}} \tag{23}$$

(3) When the electric vehicle arrives, if there is an idle charger, it can immediately receive service, otherwise it will queue up and wait. The service rule is FCFS, and the waiting space is infinite.

$$W_q = \frac{(c\rho)^c \rho}{c!(1-\rho)^2 \lambda}\left[\sum_{n=0}^{c-1}\frac{\rho^n}{n!} + \frac{\rho^c}{c!(1-\rho^c)}\right]^{-1} \tag{24}$$

3. VEHICLE CHARGING PILE PLANNING MODEL FOR HIGHWAYS

3.1 Objective Functions

(1) The annual investing construction and operation and costs of maintenance of vehicle charging pile on the high-speed road network are minimized as in,

$$\min C = C_{cstr} + C_{opm} \tag{25}$$

Where: C is the cost of the charging pile about construction and operating; C_{cstr} is the construction cost of the charging pile; C_{opm} is the annual operation and maintenance cost of the charging pile.

1) construction investment cost

The construction cost of the charging pile mainly consists of fixed costs and vary costs. The unchanging cost consists of the cost of distribution transformers, cables, active filters, battery maintenance equipment, etc.; the variable cost is mainly the cost of charger configuration.

$$C_{cstr} = \frac{r_0(1+r_0)^z}{(1+r_0)^z - 1}\sum_{i=1}^{N_{cs}}(c_b + N_i^{cp} c_{cp}) \tag{26}$$

Where: N^{cs} is the number of EV charging piles; c_b is the cost of each charging pile; N_i^{cp} is the number of chargers in the i th substation; c_{cp} is the unit value of charger; r_0 is the discount rate, and z is the number of operation year.

2) Annual operation and maintenance costs

$$C_{opm} = \frac{\eta r_0(1+r_0)^z}{(1+r_0)^z - 1}\sum_{i=1}^{N_{cs}}(c_b + N_i^{cp} c_{cp}) \tag{27}$$

(2) The max daily charging time for vehicles as in

$$\min T_{ch} = \sum_{i=1}^{N_{cs}}\sum_{j=1}^{T} W_{i,j}^q k_{pen} \alpha_{arr} q(x_i, t_j)\tau \tag{28}$$

Where: T is time for waiting of EVs; $W_{i,j}^q$ is the i th average time for waiting of EVs in the first simulation period at the j th charging pile; and τ is the simulation length of each period.

3.2 Restrictive Conditions

(1) Charging pile distance constraint

In order to guarantee the driving of vehicles, the length between neighbouring charging piles should be less than range of vehicles; at the same time, the proximity of charging piles will lead to a waste of resources.

$$l_{\min} \le d_{ij} \le l_{\max} \tag{29}$$

Where: d_{ij} is the length between the charging pile and the j th charging pile; $l_{\min}$ is the minimum spacing; $l_{\max}$ is the maximum spacing constraint.

(2) Waiting time constraint

Promoting the popular application of vehicles, the charging pile should be able to serve electric vehicle charging better, so the time for vehicle charging should be less than the user's tolerance limit.

$$W_q \leq T_{\mathrm{lim}\,it} \tag{30}$$

Where: T_{limit} is the maximum tolerance limit of waiting for EV users.

3.3 Model Solutions

The two objective functions represent the goals of the two interested parties, the charging pile builder expects to minimise the construction investment cost under the constraints, while the EV users want to have enough charging facilities and the travel time cost to be as small as possible. Therefore, the two objective functions cannot be optimal at the same time. In this paper, the multiple objective particle swarming algorithm is used to solving the above multiple objective planning problem on the Pareto frontier:

Step 1: Initialisation. Input the road parameters, O-D matrix; seting the parameters of the multiple objective particle swarm algorithm;

Step 2: Random initialisation to get a particle swarming, set the particle speed to 0;

Step 3: Carry out dynamic simulation of traffic based on road segment transmission modeling and calculate flow of traffic;

Step 4: Calculate the time of waiting of each charging pile based on queuing theory;

Step 5: Determine if the constraints are satisfied;

Step 6: Determine whether convergence or the max num of iterations is reach: if so, return the optimal solution set in the archive and stop iteration; if not, update the particle position and velocity, and return to step 4.

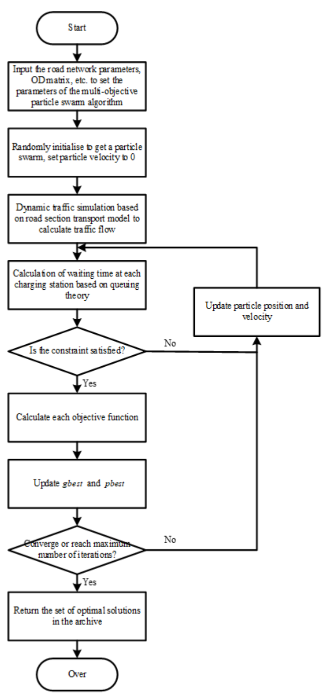

Figure 2.Multi-objective Particle Swarm Algorithm for Pareto Frontier Flowchart

4. CASE STUDY

4.1 Basic Data

The circular expressway network is shown in Figure 3, with a total of 5 toll gates (entrances and exits) and a total mileage of 465km.

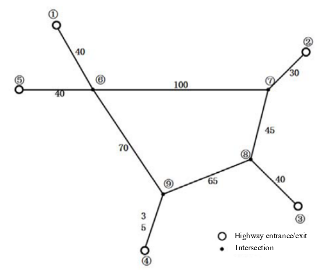

Figure 3. Example of Ring Expressway Network Calculation

The average distance between charging piles is 50km, and it is estimated that a total of 20 charging piles will need to be built on the highway network. The penetration rate of vehicles in the planned target year is 10%. Assuming that electric vehicle owners randomly choose highway charging piles for charging, in order to meet the travel needs of vehicles and reduce concerns about electric vehicle battery depletion, this article assumes that on average, highway electric vehicle owners need to charge once every three charging piles, which is the comprehensive driving rate of vehicles at highway charging piles. At this point, the comprehensive driving rate matches the range of vehicles, which can almost 100% meet the charging needs of vehicles.

The simulation node parameters of the high-speed road network in this article are shown in Table I.

Table I. Node parameters of highway network.

Node number	Node abscissa/km	Node ordinate/km
1	40	135
2	180	120
3	175	35
4	90	10
5	20	100
6	60	100
7	160	100
8	150	60
9	100	40

The parameters of the highway network section are shown in Table II.

Table II. Highway network section parameters.

Road number	Starting node	Terminal node	Length/km	V_f/(km/h)	q_{max}/(veh/h)	ρ_{max}/(veh/km)
1	1	6	40	120	6000	375
2	6	7	100	120	6000	375
3	7	8	45	120	6000	375
4	8	9	65	120	6000	375
5	9	6	70	120	6000	375
6	5	6	40	120	6000	375
7	7	2	30	120	6000	375
8	8	3	40	120	6000	375
9	9	4	35	120	6000	375

4.2 Analysis of results

Using the spatiotemporal distribution results of traffic flow obtained from the above traffic simulation as input, the previous model establishes a multi-objective planning model for charging piles. Taking an external archive size of 100, a population of 50 particles, and a maximum number of iterations of 500, the Pareto frontier of the non inferior solution planning scheme is obtained by solving the model using multi-objective particle swarm optimization algorithm, as shown in Figure 4.

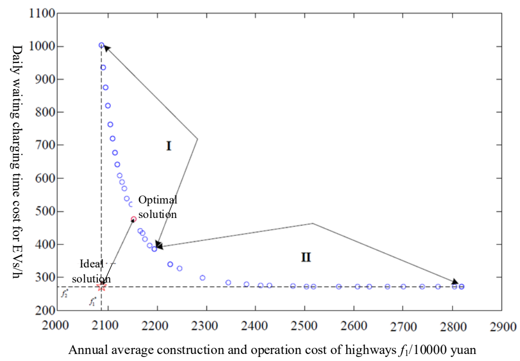

Figure 4. Pareto Frontiers and Ideal Solutions for Charging pile Planning Schemes

From the above figure, it can be seen that the time of waiting cost and annual construction and operation cost of vehicles cannot reach the optimal level simultaneously. As the annual construction and operation costs of charging piles increase, the time of waiting cost of vehicles first significantly decreases (Zone I), but further increases the annual construction and operation costs of charging piles. The improvement in waiting time cost of vehicles is relatively small but has not converged to zero (Zone I).

Use the VIKOR method to rank the Pareto frontiers mentioned above and find the optimal solution. Use f1 to represent the average annual construction and operation cost of highways, and f2 represent the daily waiting charging time cost of vehicles. When planning highway charging piles, the decision-maker is the construction party, who tends to consider the convenience of user charging while minimizing the construction and operation costs. Therefore, the weight coefficients β=[0.75,0.25]^T, v=0.5 used in this article. The ideal solution F^*=(2086.08, 271.26) was calculated using equation (2-49), as shown by the red star in Figure 4. The S, R, and Q values of each non inferior solution on the Pareto front were sequentially calculated. Sorting based on the Q values, including the comparison of the six optimal solutions, is shown in Table III.

Table III. VIKOR method sorting results.

		f_1/10000yuan	**f_2/10000yuan**	**Q**	**S**	**R**
Planning Plan Number	1	2156.56	467.47	0	0.1391	0.0721
	2	2128.37	606.04	0.0462	0.1576	0.1143
	3	2104.88	763.63	0.1102	0.1873	0.1681
	4	2086.08	1003.48	0.222	0.25	0.25
	5	2405.57	277.29	0.3434	0.329	0.3269
	6	2461.95	272.8	0.4319	0.3852	0.3846
Sort		4,3,2,1,5,6	6,5,1,2,3,4	1,2,3,4,5,6	1,2,3,4,5,6	1,2,3,4,5,6

From the analysis of the calculation results in Tables III, it can be seen that Scheme 1 ranks best according to the comprehensive value Q, and Scheme 1 still ranks first in the S and R values. According to VIKOR theory, Scheme 1 can be selected as the optimal solution among all non inferior schemes.

The position of the optimal solution (2156.56, 467.47) in the Pareto front is shown in the red circle in Figure 5. From Figure 4, it can be seen that Option 1 is not the point on the Pareto front with the shortest distance from the ideal solution, because the weights of each criterion are different; At a weight of β=[0.75,0.25]^T, the weight of construction and operation costs is greater than the weight of waiting time for vehicles. Therefore, according to the VIKOR theory, the optimal solution obtained is closer to the vertical axis, where the annual construction and operation costs are lower and the daily charging waiting time is larger. It is the feasible solution closest to the ideal solution on the Pareto front under the weight of this criterion.

The station location results corresponding to the above optimal planning scheme 1 are shown in Figure 5. The number of charging piles configured under the optimal planning scheme is shown in Table IV, and the station location coordinates are shown in Table V.

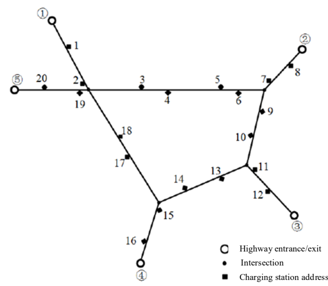

Figure 5. Location Map of the Optimal Planning Scheme

Table IV. Number of charging pile charging piles configured.

Station address label	Number of charging piles	Station address label	Length/km	Number of charging piles	Station address label	Number of charging piles
1	47	8	50	15	50	1
2	50	9	27	16	50	2
3	27	10	26	17	37	3
4	27	11	29	18	38	4
5	28	12	28	19	23	5
6	27	13	38	20	28	6
7	50	14	40			7

Table V. Location coordinates of charging piles under optimal planning scheme.

Station address label	Station coordinates/km	Station address label	Station coordinates/km
1	(47.5,121.9)	11	(153.1,56.9)
2	(57.5,104.4)	12	(162.5,47.5)
3	-90,100	13	(134.6,53.8)
4	-105,100	14	(115.4,46.2)
5	-135,100	15	(98.6,35.7)
6	-145,100	16	(92.9,18.6)
7	(163.3,103.3)	17	(82.9,65.7)

In actual transportation networks, due to differences in users' travel OD needs, they are coupled and affect each other in the network, resulting in different distribution of traffic flow on different road sections at different times. Based on the results of traffic flow simulation in Figure 4, it can be seen that in places with high traffic flow, such as stations 1,2,7.8,15,16 on road sections near large cities, there are more chargers configured; In places with low traffic flow, such as stations 11,12,19,20 on the road leading to small cities, there are fewer charging pile configurations.

In summary, this article takes into account the coupling effects of dynamic traffic simulation and OD, and the number of charging piles obtained matches the traffic flow. The planning results are more economical and reasonable, and can well meet the charging needs of vehicles.

5. CONCLUSIONS

Through the analysis of highway network examples, it is shown that the method based on dynamic traffic simulation in this article can accurately consider the dynamic travel demand between different urban OD pairs and the spatiotemporal impact of typical traffic flow characteristics on the queuing process of vehicles at charging piles. The number of charging piles configured at charging piles matches the traffic flow of the road section in which they are located, and the number of charging piles in high traffic sections is also large to meet the charging needs of vehicles; By using multi-objective particle swarm optimization algorithm to solve the model, Pareto frontiers with relatively uniform distribution can be obtained. The optimal planning scheme determined by VIKOR method has a uniform distribution of station locations, which can simultaneously consider the investment cost of charging pile construction and the convenience of electric vehicle charging services, and has a wide range of practicality.

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