Route Planning and Charging Navigation Strategy for Electric Vehicles Based on Real-time Traffic Information and Grid Information

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Abstract. Aiming at the characteristics of Electric Vehicles (EVs) combined with transportation and mobile load, and their charging and driving behaviors will interact with the traffic system and power grid system. On the basis of this, a route planning and charging navigation strategy for EVs based on real-time traffic information and grid information was presented in this paper. First, a dynamic traffic network model was established according to the time-varying feature of traffic information. And also, the road resistance model with road segment impedance and intersection node impedance was proposed depending on the attribute of urban roads. Furthermore, based on the establishment of traffic network model, distribution network model and single EV model, a multi-objective optimization function integrated with the road travel time, the charging station load and the quantity of vehicles entering into the station was determined, which was solved to recommend the optimal driving and charging paths by dynamic Dijkstra dynamic search algorithm. At last, the actual road network of a certain zone in Nanjing was selected as an example to analyze the spatial-temporal distribution of EV charging load, and evaluated the impact of its charging and driving on traffic network and distribution network. Simulation results demonstrate its effectiveness and feasibility.

1. Introduction
With the adjustment of the world energy industry structure and people's constant attention to environmental issues, the environmental pollution and reliance on resources of fossil fuels caused by the development of automobile industry are all challenging concerns of the present world [1]. Alternative fuel vehicles, especially the plug-in electric vehicles (PEVs), are considered as an emerging solution to these aforementioned challenges, and thus providing an attractive perspective of transportation sectors and power departments [2].

However, the driving and charging characteristics of multitude EVs will have a certain impact on power grid operation and traffic congestion [3]. Therefore, an effective charging scheduling strategy is adopted to plan the optimal driving path and recommend the reasonable Charging stations (CS) for individual EV, which can reduce the owner’s range anxiety caused by battery capacity limitation, and ameliorate the influence of EV driving and charging process on power grid and traffic network[4].

As regards the charging scheduling strategy for the interaction between EVs and power grid, with the proposal of V2G (Vehicle to Grid) technology [5], various scholars have developed the orderly charging scheduling methods from the perspective of optimizing the operation of power grid and improving the interests of owners [6]. Yagcитеkin et al. [7] presented a double-layer smart charging management algorithm (SCMA) for EVs based on charging safety factors. On the premise of
satisfying both power grid and drivers’ requirements comprehensively, this approach decreased the charging costs and prevented the overloading of transformers. Mo et al. [8] addressed the impact of EV charging on power quality of distribution network, and proposed an optimal EV rapid charging navigation strategy based on the internet of things network. Xu et al. [9] established a hierarchical control charging model, and analyzed the defining relationship among the different interactive systems via multiple time scales. The optimization strategy was adopted to improve the resource utilization rate of charging stations and reduce the unbalanced distribution of charging loads.

On the other hand, given the charging scheduling strategy for the interaction between EVs and traffic network, researchers mainly focus on charging navigation and path guidance for vehicles combining with traffic network information and charging infrastructure layout. In [10], a hierarchical navigation strategy based on dynamic data was proposed, considering the scenarios with traffic network information and ambient temperature. In [11], an analysis technology with big data was utilized to mine the taxi travel dataset and recommend charging stations for vehicles with charging requirements in real-time. In [12], an effective charging navigation strategy was formulated for EVs driving on the expressway, which aims to reduce the travel time and charging time cost.

In summary, although the above two types of charging scheduling strategies have achieved some results, they are only independent research from the interaction mechanism between EVs with power grid system or traffic system. However, the charging and driving behaviors of EVs are closely coupled with the power grid and traffic network, which will be affected by the interaction of power grid operation status and traffic flow information simultaneously. Accordingly, Guo et al. [13] constructed a charging path navigation architecture that integrated grid information and traffic information. It pushed the charging station capacity information to each owner through the Intelligent Transport System (ITS) and guided it to charge quickly. However, the proposed model failed to present an optimal path recommendation scheme for an EV. Furthermore, Mu et al. [14] proposed a charging load forecasting method based on the Vehicle-Road-Grid fusion model. Origin Destination (OD) method was adopted to model EVs with different functions, and the distribution network power flow analysis was carried out by integrating traffic and grid information. However, the established traffic network model did not consider the impact of impedance delay at road network intersections. Under the Vehicle-Road-Grid fusion framework, other researchers [15] optimized the EV charging path, which reduced the road congestion caused by aggregation charging and improved the space-time distribution of charging station loads. However, the traffic side model was a static road network without considering the real-time dynamic characteristics of traffic information.

Therefore, this paper proposed an EV path planning and charging navigation strategy integrating real-time traffic information and grid information. Firstly, the dynamic traffic network model, the distribution network model and the single EV model were established respectively. And also, the comprehensive road resistance target of navigation method was determined, and the multi-objective path planning problem was solved by dynamic Dijkstra algorithm. Finally, the actual road network of Nanjing was taken as an example to analyze the temporal-spatial distribution as well as the interactive influence of charging loads, and verified the implementation effect of the proposed strategy.

2. Electric vehicle - distribution network - transportation network interaction model

2.1. Dynamic traffic network model

Transportation network bears all the trip requirements, which is the basis of route planning and navigation. Due to the dynamic time-varying characteristics of traffic information, graph theory analysis method [15] was adopted to model and describe the traffic network:

\[
G^T = (V, E, K, W) \\
V = \{v_1, v_2, v_3, \ldots, v_n \} \quad E = \{v_i, v_j \in V, v_i \neq v_j \} \\
K = \{k | k = 1, 2, 3, \ldots, m \} \quad W = \{w_{v_i, v_j}, v_i \in E, k \in K \}
\]
where, $G^T$ denotes the traffic network; $V$ denotes the set of all nodes in $G^T$, namely, the set of intersection nodes; $E$ denotes the set of all directed arcs in $G^T$, namely, the set of road segments in the traffic network; $W$ denotes the set of road segment weights; $K$ denotes the set of time periods.

Aiming at most of the urban traffic road network nodes are equipped with signal lights. The time consumption of vehicles in the driving process is affected not only by the road impedance on the arc, but also by the time delay caused by the control of signal lights at intersections. Therefore, the road resistance consists of the road segment impedance and intersection node impedance, the urban road resistance model can be expressed as follows:

$$w^k(t) = C_v(t) + R_v(t)$$

where: $C_v(t)$ represents the intersection node impedance model, $R_v(t)$ represents the road segment impedance model.

According to the urban traffic condition classification standard, the road traffic condition was divided into four grades by the saturation $S$ evaluation index [16]: Unblocked ($0 < S \leq 0.6$), Slow ($0.6 < S \leq 0.8$), Congestion ($0.8 < S \leq 1.0$) and Serious Congestion ($0.8 < S \leq 1.0$). The models corresponding to different saturation are as follows:

1) Road segment impedance

$$R_v(t) = \begin{cases} R^1_v(t) & : |S - S_k| \leq 0.05, 0 < S \leq 1.0; \\ R^2_v(t) & : |S - S_k| > 0.05, 1.0 < S \leq 2.0 \end{cases}$$

where: saturation $S = \frac{Q}{C}$: $Q$ is the traffic flow of a road segment, and $C$ is the traffic capacity, $t_0$ is the zero-flow travel time, $\alpha$, $\beta$ are the impact factors of the impedance model.

2) Intersection node impedance

$$C_v(t) = \begin{cases} C^1_v(t) & : 0 < S \leq 0.6; \\ C^2_v(t) & : \frac{c(1-\lambda)^2}{2(1-\lambda S)} + \frac{S^2}{2q(1-S)}, \quad 0.6 < S \leq 1.0; \\ C^3_v(t) & : \frac{c(1-\lambda)^2}{2(1-\lambda S)} + \frac{1.5(S-0.6)}{1-S}, \quad S > 0.6 \end{cases}$$

where: $c$ is the cycle length; $\lambda$ is the green split; $q$ is the vehicle arrival rate of the road segment.

From equation (3) and equation (4), it can be known that saturation $S$ is the only dynamic variable in the above-mentioned impedance model, and the remaining parameters are the inherent attribute values of road design and planning. Finally, according to the saturation level of the traffic network, the intersection node impedance and road segment impedance were combined to obtain the dynamic road resistance model of the urban road network:

3) Dynamic road resistance model

$$w^k(t) = \begin{cases} R^1_v(t) + C^1_v(t) & : 0 < S \leq 0.6; \\ R^2_v(t) + C^2_v(t) & : 0.6 < S \leq 0.8 \\ R^3_v(t) + C^3_v(t) & : 0.8 < S \leq 1.0; \\ R^4_v(t) + C^4_v(t) & : 1.0 < S \leq 2.0 \end{cases}$$

2.2. Distribution network model

In order to match the scale of the transportation network, it is necessary to establish a certain scale and level of the distribution network. In this paper, the distribution network model based on the IEEE-33 nodes was selected, and the fast charging station was connected to the distribution network through 10/0.4 kV distribution transformer. The distribution network model is as follows:

$$D_p = (N_p^v, B_p^v, G_p^v)$$

where: $N_p^v$ denotes parameters such as node type, power and voltage; $B_p^v$ denotes parameters such as branch connection, resistance and transmission power; $G_p^v$ denotes information such as location and capacity of the source node.

Further, the total charging load $P_k$ of the distribution network node $K$ at each moment was the cumulative power of the recharging vehicles at the charging station.
\[ P_i = \sum_{j=1}^{N} P_{ij} \]  

where: \( N \) represents the total number of recharging vehicles at time \( t \), and \( P_{ij} \) represents the charging power of the \( i \)th vehicle at time \( t \).

### 2.3. Single Electric Vehicle model

In terms of the EV charging and driving characteristics, the modeling and analysis of single electric vehicle were carried out:

1) Initial location information

The EVs were uniformly numbered \( N_e = \{i | i = 1, 2, 3, K, n\} \), and \( n \) represents the quantity of these introduced vehicles. OD starting and ending matrix method was adopted to simulate vehicles driving process [14], that is, the OD matrix was deduced by the change of traffic flow in each period of a road segment. For each EV introduced, its departure location \( D_r(i) \), arrival location \( D_a(i) \), departure time \( t_r(i) \) and arrival time \( t_a(i) \) were assigned via Monte Carlo Sampling [9]. OD starting and ending matrix probability matrix are as follows:

\[ C_{ij}^K = \frac{Q_{ij}^K}{\sum_{j=1}^{n} Q_{ij}^K} \quad (1<i<n, 1<j<n, i \neq j) \]  

where: \( b_{ij}^K \) denotes the traffic flow \( Q \) between initial traffic node \( i \) and destination node \( j \) in the \( K \)th time period, and \( C_{ij}^K \) denotes the travel probability between the two nodes.

2) Battery energy information

We selected BYD E6 as the EV simulation model and referred to its technical index: battery capacity is 24 kW·h, the endurance mileage is 160 km under operating conditions, and the power consumption per kilometer is about 0.16 (kW·h)/km. According to China’s QC/T 841-2010 ‘Electric Vehicle Conductive Charging Interface’ charging facility standard, the fast charging power was deployed as 50 kW (L3 level). In order to prevent battery damage caused by overcharging, the State of Charge (SOC) of EVs after finishing charging was set as 0.8~0.9 [13], and then the battery capacity at the initial time was \([0.8\sim0.9\cdot B_f(i)] \) kW·h. Assuming that the EV power consumption increases linearly with the travel distance [12], then the remaining battery capacity \( B_i(i) \) at time \( t \) is:

\[ B_i(i) = \eta(B_{i-1}(i) - \Delta t \cdot E_c) \]  

where: \( \eta \) denotes the energy consumption coefficient; \( B_{i-1} \) denotes the remaining battery capacity at time \( t-1 \); \( \Delta t \) denotes the distance of the \( i \)th vehicle traveled from time \( t-1 \) to time \( t \).

3) Charging demand information

When the remaining battery capacity \( B_i(i) \) satisfies any condition of equation (10), the charging demand will be triggered:

\[ \begin{cases} B_i(i) \leq \varepsilon \cdot B_i(i) \\ B_i(i) \leq L_{\text{ch}}(i) \cdot E_c \end{cases} \]  

where, \( \varepsilon \) is owners’ range anxiety coefficient, uniform distribution \( \varepsilon \sim [0.15,0.3] \) [6]. \( L_{\text{ch}} \) denotes the distance from current location \( D_r(i) \) to destination \( D_a(i) \). That is, when the remaining battery capacity \( B_i(i) \) is lower than the initial set threshold or cannot reach the destination, the charging demand is generated.

Dynamic Dijkstra path search algorithm [17] was adopted to plan the driving route for vehicles and recommend a charging station for the EV with charging demand.

\[ N_{e,i} = \begin{cases} 1, Ch(i) = 1 \\ 0, Ch(i) = 0 \end{cases} \]
where: \( j = 1, 2, 3, K_m \), \( m \) represents the number of charging stations, and \( Ch(i) \) represents the charging demand marker. When the EV has a charging demand, it is set to 1; otherwise, it is set to 0.

4) Dynamic driving information

The time from starting position \( D_v(i) \) to recommend charging station position \( D_v(i) \) of a vehicle through the path search algorithm was the accumulation of road resistance \( W \) of actual driving paths:

\[
T_v(i) = t_v(i) + \sum_{v_g \in E} \left[ v_g \cdot w^g(t) \right]
\]

(12)

where: \( v_g = 1 \) indicates that the vehicle is in the actual driving path, otherwise it is 0. The road resistance model was calculated according to equation (5) of the actual traffic information.

The waiting charging time was the difference between the charging finish moment of the vehicle \( k \) reached CS at the latest and the moment when the current vehicle \( I \) reached CS:

\[
T_v(i) = t_v(k) - t_v(i)
\]

(13)

The charging finish moment was the sum of the vehicle’s arrival moment, charging waiting time and charging time:

\[
t_d(i) = t_v(i) + T_v(i) + T_c(i)
\]

(14)

The charging time \( T_c(i) \) was obtained by equation (15):

\[
T_c(i) = \frac{B_v(i) - B_v(i)}{\eta_v \cdot P_c}
\]

(15)

where: \( \eta_v \) represents the charging efficiency, ranging from 0.8 to 0.9.

The number of vehicles in charging station \( M_v(j,t) \) at time \( t \), included the charging vehicles and waiting for charging vehicles:

\[
M_v(j,t) = \sum Cs(j,i,t_v)
\]

(16)

where: \( Cs(j,i,t_v) \) means the \( i \)th vehicle staying at the recommended \( j \)th charging station at the time \( t_v \).

3. Electric vehicle path planning and charging navigation method

In the interactive architecture model, in order to integrate the three information and formulate a comprehensive goal for path planning and charging navigation, we coupled the respective objective of EVs, power grid and transportation network to obtain a comprehensive road resistance function \( W_G \).

3.1. Comprehensive road resistance function

1) EV target road resistance function

In the light of the statistical analysis results [17], travel time is the most concerned factor for owners. Therefore, the travel time \( t_v(i) \) from the initial position \( D_v(i) \) to charging station position \( D_v(i) \) was chosen as the EV target road resistance \( W^E \):

\[
W^E = t_v(i) + \sum_{v_g \in E} \left[ v_g \cdot w^g(t) \right]
\]

(17)

2) Power grid target road resistance function

Power grid side mainly considers the safe and economic operation of the system as its measurement index, so the charging station load \( P_i \) connected to the distribution network was chosen as the target road resistance \( W^P \):

\[
W^P = P_i = \sum_{j=1}^{K} P_{ij}
\]

(18)

3) Transportation network target road resistance function

To reduce the traffic segment congestion around CS caused by EV gathering and charging, the number of charging vehicles \( M_v(j,t) \) at CS was chosen as its target road resistance \( W^T \):
Finally, the comprehensive road resistance function $W^G$ of each single target was determined by weight coefficients:

$$
W^G = \mu_1 \frac{W^E}{\min(W^E)} + \mu_2 \frac{W^P}{\min(W^P)} + \mu_3 \frac{W^T}{\min(W^T)}
$$

where: $\mu_1$, $\mu_2$ and $\mu_3$ respectively represent the weight coefficients, $W^E$, $W^P$ and $W^T$ independently optimize the results of travel time, charging station load and the number of vehicles at charging station without considering the other two objectives. It can be seen that the optimal charging strategy recommends the charging station with short travel time, low charging load and few incoming vehicles.

### 3.2. Constraint conditions

To ensure the rationality of charging navigation strategy, the constraints are given as follows:

1) EV charging constraints

The mileage of recommended charging stations for EVs with charging demand should be within the range of remaining electricity:

$$B_i(i) \leq L_n(i) \cdot E_c$$

where: $L_n(i)$ represents the distance from the vehicle's current position $D_i(i)$ to CS position $D_n(i)$.

2) Grid operation constraints

The charging station load at each moment should be less than the set threshold:

$$P_i(j,t) < P_{th}(j,t)$$

where: $P_i(j,t)$ denotes the load of the $j$th charging station at time $t$; $P_{th}(j,t)$ denotes the load threshold of the $j$th charging station at time $t$.

Similarly, to ensure the safe operation of the distribution network, the voltage offset rate of each node should be within a reasonable range:

$$|N_v(k,t)| < 7\%$$

where: $N_v(k,t)$ represents the voltage offset rate of the $k$th node at time $t$ in the distribution network.

3) Traffic road travel constraints

To avoid the traffic jam, the driving speed of the recommended road segment should be restricted:

$$V_c(i,t) \geq 30\%V_0; \quad V_c(i,t) = \frac{L_y}{R_v(i,t)}; \quad V_0 = \frac{L_y}{t_0}$$

where: $V_c(i,t)$ represents the average travel speed of actual segment, $V_0$ represents the average travel speed at zero-flow, and $L_y$ represents the length of the road segment $v_y$.

### 4. Path planning and charging navigation flowchart

Figure 1 shows the EV path planning and navigation flowchart, the whole process is as follows:

Update of information parameters: Firstly, the system initializes the real-time information of EVs, power grid and traffic network, and reads the initial parameters of EV position and battery energy.

Driving path planning: The system judges the charging demand marker, and when the charging demand is not triggered, the goal is to drive with the minimum road resistance $w^G(t)$, that is, the minimum travel time-consuming. Dynamic Dijkstra algorithm is utilized to calculate road resistance information, and three driving routes are recommended for the owner, who randomly chooses any route to drive. Current position $D_i(t)$ and speed of each vehicle $V_i(t)$ are recorded, the remaining battery capacity $B_i(t)$ is updated after reaching the destination, and the travel path planning is completed.

Charging path navigation: Once the charging demand triggers, the minimum comprehensive road resistance is taken as the charging navigation target. The road segment is assigned by calculation $W^G$, etc.
and the dynamic Dijkstra algorithm is adapted to search and recommend three charging paths. The owner randomly chooses any route to drive for recharging. When an EV arrives at a station, the number of vehicles at the station and their arrival time $t_a(i)$ are counted. Vehicles are charged with constant power $P_i$. Determine whether the charging is completed or not, and if it is completed, change the travel position to destination position $D_{di}(i)$ again, so that the travel route navigation planning can be carried out with the least travel time-consuming until the destination is reached.

System scheduling judgment: All vehicles introduced are judged by charging schedule. When all those vehicles complete path planning and charging navigation, they exit the scheduling.

![Flowchart of EV path planning and charging navigation](image)

**Figure 1.** Flowchart of EV path planning and charging navigation.

5. Case studies and analysis

5.1. Actual road network model

To verify the implementation effect of the charging navigation strategy proposed, the actual road network was selected for modeling and analysis. It was divided into residential areas (RA), commercial areas (CA) and industrial areas (IA) according to the standard of the traffic function area. Figure 2 shows the road network topology diagram of a certain area in Nanjing. As depicted, the total area is about 48.8 km², and the circumference is about 27.9 km, including 103 intersection nodes and 158 major road segments. The model parameters and real-time traffic information can refer to our previous research in [18].
order to match the scale of the above mentioned traffic network, we established three distribution network models of IEEE-33 nodes. The charging stations are connected to the distribution network through nodes, whose load threshold is 2 MW and the prescribed capacity is 30 vehicles.

5.2. Analysis of simulation results

Firstly, we started from the overall optimization of the system and did not study the influence of weight coefficient on the results in depth. Thus, the weight coefficients were uniformly set as 1/3. Figure 3(a) and Figure 3(b) show the spatial and temporal distribution of all-day charging demands.

As revealed by Figure 3, on the whole, the temporal distribution of charging demands is not uneven. Their peak time periods occur in 11:00-12:00 and 16:00-17:00. Residential peak concentrates in 11:00-12:00 and 16:00-17:00, industrial peak concentrates in 12:00-13:00 and 17:00-18:00, and commercial peak concentrates in 13:00-14:00 and 17:00-18:00. The temporal distribution of charging demand is consistent with the rule distribution of residents’ trips.

In terms of spatial distribution, there are some differences according to the types of functional areas. The number of vehicles needed for recharging in commercial areas is the largest, with an average number of 45.56 vehicles, followed by 32.15 vehicles in residential areas, and the least in industrial areas, with an average number of 19.42 vehicles.

5.2.1. Analysis of single EV charging navigation path. Based on the charging demand distribution, to describe the EV charging navigation path, the EV numbered Ne(12587) was selected for path
analysis. Its OD positions are node 9 and node 74, travel time is at 08:15. Meanwhile, the driving path of disorderly charging method is compared with our optimal driving path which is planned according to the goal of the shortest distance for vehicles. The nearest charging station is recommended for an owner when the charging demand is triggered. The analysis results are listed in Table 1.

| Method             | Actual route                                                        | Recommended CS | Driving mileage/km | Travel time/min | Charging waiting time/min | Charging station load/MW | Number of vehicles at station |
|--------------------|---------------------------------------------------------------------|----------------|-------------------|-----------------|--------------------------|--------------------------|------------------------------|
| Disorderly route   | 9→10→11→19→20→28→30→31→39→40→48→61→74                           | CS2            | 6.2               | 34.55           | 8.8                      | 1.75                     | 48                           |
| Optimal route-1    | 9→10→18→19→20→29→31→39→40→48→61→74                              | CS3            | 9.1               | 21.78           | 4.1                      | 1.30                     | 24                           |
| Optimal route-2    | 9→10→18→25→26→37→52→37→38→48→61→74                              | CS5            | 10.8              | 25.34           | 6.8                      | 1.15                     | 18                           |
| Optimal route-3    | 9→16→17→19→27→28→29→31→39→40→48→61→74                           | CS3            | 12.7              | 27.88           | 4.6                      | 1.35                     | 27                           |

As depicted, although the disorderly charging method achieves the least driving mileage, compared with the optimal charging method, it does not avoid congested roads and takes a long time, which exceeds 36% of that average value. And CS2 is recommended nearby for recharging, whose charging load is close to the limit threshold, and the number of vehicles at the station exceeds the limit capacity by 18. However, the three recommended paths by the optimal method have less travel time and average waiting time of 5.1 minutes. Although it is in the morning peak period, the indexes tend to be saturated, but they are within the controllable capacity range.

5.2.2. Analysis of power grid impact. And then, the influence of charging behaviors on the distribution network was analyzed. Load distribution of each charging station under disorderly method and optimal method are shown in Figure 4(a) and Figure 4(b).

![Charging station load obtained by disorderly method and optimal method.](image)

(a) Charging station load of disorderly method. (b) Charging station load of optimal method.

Figure 4. Charging station load obtained by disorderly method and optimal method.

From Figure 4(a) and 4 Figure(b), under the disorderly charging strategy, the distribution of loads is uneven and the peak-valley difference of each station is large. Among them, the maximum load is CS11 with 2.45 MW at 09:30, which is beyond the limit threshold, the minimum load is CS4 with 0.20 MW at this time. Meanwhile, under the optimal charging method, the CS11 load is reduced to 1.55 MW and the lowest CS4 load is increased to 0.35 MW, which reduces the load peak-valley difference.

5.2.3. Analysis of traffic network impact. At last, the traffic travel capacity of the road segment was evaluated. Figure 5 shows the change of the average traffic speed of road segment [57-58] near the
CS5. It can be seen that the speed of vehicles in the road segment [57-58] is low between 07:00-10:00 and 18:00-21:00. Under the disorderly strategy, the proportion of time range below the zero-flow average speed is 47.8 %, and the optimal strategy is 27.6 %. Therefore, the optimal strategy by traffic side optimization improves road trip efficiency.

![Figure 5. Average speed of vehicles in the road segment [57-58].](image)

6. Conclusions
This paper proposed an EV path planning and charging navigation strategy, and established a dynamic traffic network model, distribution network model and single EV model respectively. Finally, taking a specified regional road network and the distribution network as examples, the validity of this strategy was verified by simulation tests. The most important results of the proposed approach are as follows.

1) The proposed interactive model and navigation strategy recommends the optimal path based on real-time road information, which can be used as a navigation algorithm to plan the driving path, and also can reasonably recommend charging station through integrated road resistance search.

2) The charging navigation strategy combining real-time traffic information and grid information, provides three driving and charging routes simultaneously, effectively diverts traffic flow, and avoids road congestion, as well as improves traffic system operating condition.

3) The optimal strategy reasonably controls the number of charging EVs and effectively dispatches the load resources of charging stations. It not only shortens the waiting time for recharging, but also improves the economy and security of charging stations.

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