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A Hierarchical Navigation Strategy of EV Fast Charging Based on Dynamic Scene

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ABSTRACT With the development of the EV industry, the growing demand for EV fast charging load has brought enormous impact on the power system. Due to the unbalance of charging time distribution and the high power of EV fast charging, the difference between peak and valley of the load curve will widen. In this paper, a hierarchical navigation strategy (HNS) based on dynamic traffic/temperature data is proposed to decrease the EV fast charging load at peak hours and the time and energy cost during the charging process. The upper layer of the HNS is charging time selection. The optimal selections of charging time, which is based on the habits of EV users, is proposed in this layer. It aims at providing efficient time slots for charging, which can decentralize the fast charging demand and decrease the EV users' time cost. The underlayer is the route selection layer, which is based on the priority coding genetic algorithm. It proposes the optimal charging routes to decrease EV users' energy cost and time cost. At the same time, the peak charging load can also be shaved due to the decline in energy cost. The case study under the scene with realistic traffic, temperature, and power grid information shows that the proposed HNS can shave the peak load of the power grid and decrease the energy/time cost during the EV fast charging process. Therefore, the effectiveness of the HNS is proved.

INDEX TERMS EV fast charging, peak shaving, hierarchical navigation strategy, dynamic data, priority coding genetic algorithm.

NOMENCLATURE

ABBREVIATIONS

EV	Electric vehicle
PCGA	Priority coding genetic algorithm
SOC	State of charge
DC	Data center
CC	Control center
EVFCS	EV fast charging station
SPA	Shortest path algorithm
HNS	Hierarchical navigation strategy

SYMBOLS

C_A	Energy cost of air conditioners
C_E	Energy cost of EV engines
v	Average speed of EVs
l	Travel distance of EVs
T_r	Travel time of EVs
T_{ts}	Waiting time of traffic signals
T_{cs}	Queuing time in charging stations
RH	Humidity level
t	Temperature
ΔC_T	Extra energy cost of charging process
C_{TC}	Energy cost of the charging route
C_{TO}	Energy cost of the original route
l_T	Endurance mileage of EVs
W_B	Battery capacity
Q_{car}	The power which is transferred into EV
Q_n	The power which is brought by fresh air
Q_h	The power which maintains the stable of humidity in EVs
t_0	The starting time
t_n	The ending time
Q_{car}	The power transferred through glasses
l_o	Fresh air volume
n_p	Number of passengers
ρ_a	Air density
ΔH	Enthalpy difference between in and out of EVs

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L	Fresh air volume of air conditioners
V_a	Specific volume of air
X	Absolute humidity
k_{glass}	Heat transfer coefficient of glasses
k	Heat transfer coefficient of EV bodies
S_{glass}	Area of glasses
S_{cr}	Area of roofs
S_{cs}	Area of sides
S_{cub}	Area of underbodies
T_{out}	Temperature outside EVs
T_{in}	Temperature in the EVs
s	Number of charging poles
K	Number of parking spaces for EVs to wait in line
$\lambda(t)$	Real-time arrival rate
μ	Service rate
$\rho(t)$	Service intensity of the system
$p_0(t)$	System idle probability
$p_K(t)$	Costumer loss rates
$W_q(t)$	Average queuing time of EVs
$L(t)$	Real-time number of EVs in the EVFCS

I. INTRODUCTION

In recent years, electric vehicles (EV) have become a center of attention because of its potential to be an alternative to conventional vehicles. The advantages of EVs' development include reduction of greenhouse gases emission and fossil energy consumption. Penetration of EV in some major cities in the world is growing typically in a decade [1]–[5]. At the same time, development of fast charging and ultra-fast charging skills brings convenience to EV owners [6]. However, fast charging load will increase dramatically with the rapid growth of EVs, thus will result in a huge influence on the power grid. In extreme weathers, the charging demand of EVs and base load of the power system can be enormous due to the using of air conditioners, so in these scenes, the charging load of EVs can even bring greater impact on the power system.

Various of researches about charging load of electric vehicles have been done. At the aspect of influences to the power grid, the charging behavior and impacts of fast charging load of EV were analyzed. Power and current of fast charging, especially ultra-fast charging is much higher than conventional charging. At the same time, according to EV users' charging behavior, the peak of fast charging load and the peak of the base load of the power system can appear at same time segments. So large-scale electric vehicle fast charging load will increase the peak load of power grid [7]–[13]. To solve this problem, many previous researches focused on ordered fast charging strategies which always consider the traffic process and the queuing process of fast charging. In some former studies, the randomized algorithm was used to simulate the traffic character [14]–[16], while queue algorithm was widely used to estimate the queuing time [17], [18]. Many researches aimed to decrease the charging cost and peak load through optimal control or time-of-use power prices. In [19], two charging strategies aimed to minimize the total daily cost and the peak-to-average ratio were proposed respectively, and a study compared two charging strategies was conducted from the perspectives of economic and technical. Four charging strategies focus on decreasing charging cost and peak demand were compared in [20], which considered three different charging scenarios. In [21], a real-time distributed control approach based on EV users' travel behaviors was built, which can smooth the daily grid load profile and ensure EV users' charging demand. A multi-objective optimization strategy was proposed which considered economic charging, minimizing battery degradation and maintaining system load profile in [22]. However, these researches always ignore the influence of fast charging navigation which can help EV users to choose reasonable routes and time to charge. At the aspect of decreasing peak load and smoothing load curve, EV charging navigation systems were mentioned in many previous researches [23]–[31]. Researches of the EV navigation system are an extension of classical routing. [32] presented a fast charging navigation system which took both traffic conditions and status of the power grid into consideration, this system can satisfy drivers' demands and ensure the security of the power grid at the same time. A scene of products delivering process of battery electric vehicles fleets was proposed in [33], under this scene, a mixed integer linear programming model was built to optimize the costs of maintenance and extra hours of fleets. Previous researches of EV navigation always use static traffic and weather models which unable to reflect the dynamic characteristics of scenes. At the same time, most of these researches just consider the load transferring function of EV navigation but ignore the possible peak load reduction can be brought by navigation strategy, especially in extreme weathers.

A hierarchical navigation strategy which based on dynamic traffic/weather model is proposed to make the most of possible peak shaving ability of the navigation system itself. The proposed navigation strategy is composed of two major layers: the layer of charging time selection and the layer of route selection. The upper layer can help EV users to choose efficiency time to charge according to EV users' using habit. The under layer can help EV users to choose charging stations and routes to save time and cost of fast charging with the support of real-time traffic/weather information, at the same time peak shaving in rush hours can also be achieved. The proposed strategy considers the common interests of the power system and EV users, it can achieve peak shaving of load curve and save the EV users' charging cost at the same time, so it can motivate EV users to follow the navigation strategy. This strategy can decrease the power cost that wasted on extra mileage of charging and in the charging stations, and it can also decrease the possibility of choosing inefficient charging time. The power demand of charging at rush hours will be decreased with this strategy, so that the peak load can be shaved. The effectiveness of the proposed navigation strategy will be more significantly in extreme weathers because of the load of air conditioners.

The following aspects are the main contributions of this paper:

1) A charging time selecting method based on EV users' using habit and historical traffic data is proposed to help EV users to choose efficient charging time.

2) A route selecting method for dynamic scenes is proposed based on priority coding genetic algorithm (PCGA), which considered the dynamic information of traffic, weather, EV terminals and queuing time in charging stations.

3) A detailed comparison between traditional shortest path algorithm and proposed hierarchical navigation strategy is carried out in the case study which can verify the effectiveness of hierarchical navigation strategy, especially in extreme weathers.

The remainder of this paper is organized as follows: In section II, the system architecture is introduced and the traffic/weather model, the energy cost model, the queuing model are presented. In Section III, charging time selection layer and route selection layer of hierarchical navigation strategy is presented. The case study is presented to verify the effectiveness of the proposed hierarchical navigation strategy in section IV. Finally, the conclusion is drawn in section V.

II. SYSTEM MODELING

A. PROBLEM ANALYSIS AND HYPOTHESIS

As illustrated in the introduction, the problem of EV fast charging navigation in this paper can be described as: providing an EV fast charging navigation strategy which can select charging time and charging routes for EV users to achieve peak shaving of charging load curve. At the same time, EV users' profits should also be considered to motivate them to follow the charging plans which are provided by navigation strategy. So, charging time cost and energy cost for EV charging should be decreased when following the navigation strategy.

There are two steps to achieve these goals:

1) Selecting more efficiency charging time for EV users. For power system, optimized selection of charging time can help to transfer charging load from peak period to the off-peak period so that peak shaving can be achieved. For EV users, time on roads and waiting in charging stations can also be decreased.

2) Selecting more efficient routes for EV users. Route selection can decrease charging time cost and time cost. In the peak period of charging the reduction brought by navigation strategy will decrease the real-time charging demand, so the peak of charging load will be shaved.

EV information, traffic information and weather information is necessary to solve this problem. EV information contains start point and destination of route, SOC of batteries. When EV users decide to go to EV fast charging stations, the charging process can bring extra distance to the original route so that it will increase the energy cost on the roads. Traffic information contains congestion levels of each road segments, queuing time in EV fast charging stations and traffic signals, and the information will change over time because the scenes in this paper are dynamic. So the variation of traffic information can influence the time cost of charging and the service time of air conditioners in EVs. Weather will influence the energy cost of air conditioners in EVs due to the variation of temperature and humidity.

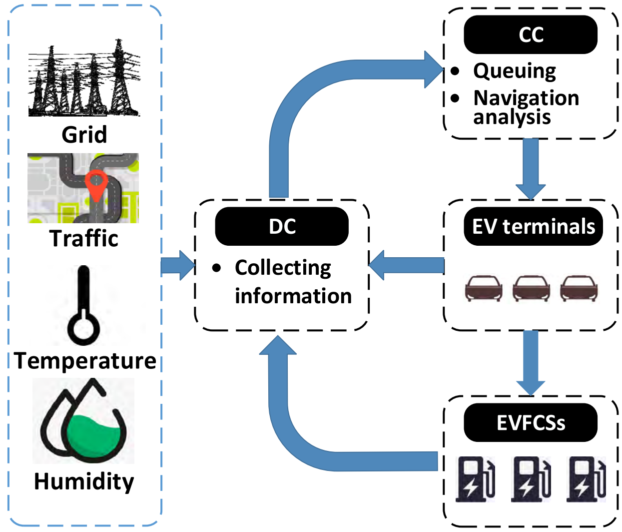

FIGURE 1. Structure of EV fast charging navigation system.

Some hypotheses in this paper are proposed as follows:

(1) All the charging stations have certain locations.

(2) All the charging stations have obligation to help the power grid shaving peak load in rush hours.

(3) EV users will choose the most energy saving routes that proposed to them

(4) EV users and conventional car users have similar travel habits.

(5) For convenience, EV users tend to charge their EVs during daily trips, rather than making special trips to go to the EV fast charging stations.

B. SYSTEM ARCHITECTURE

The structure of the proposed EV fast charging navigation system in this paper is shown in figure 1. It contains data center (DC), control center (CC), EV fast charging stations (EVFCSs) and EV terminals. The function of DC is collecting the information about traffic, weather (temperature, humidity), load, EV terminals, EVFCSs (queuing), and providing them to CC. CC is the core of this system, it is responsible for processing data from DC, analyzing the real-time load status of gird, estimating queuing time of EVFCSs, assessing priorities of each navigation plans and sending results to EV terminals. EV terminals should offer their terminal data which include average mileage, real-time SOC, time distribution of using EVs. As for EVFCSs, they should send real-time queuing data to CC to help to estimate the possible waiting time in EVFCSs.

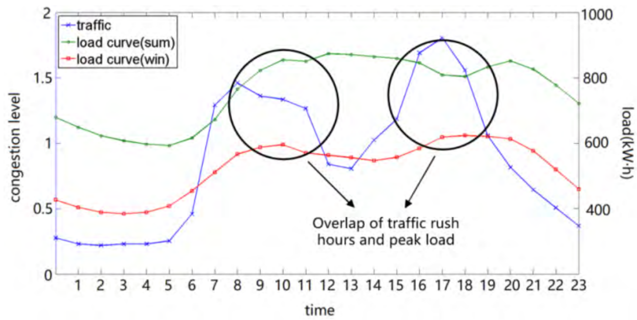

FIGURE 2. Daily load curve and curve of congestion level.

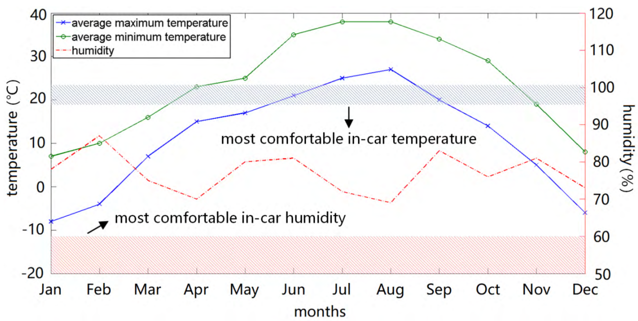

FIGURE 3. Annual temperature and humidity of Wuhan.

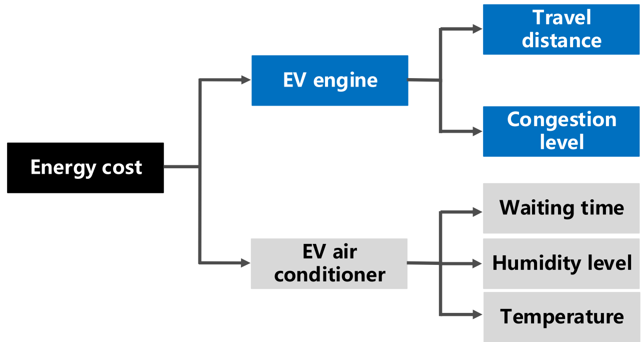

FIGURE 4. The energy cost of EV.

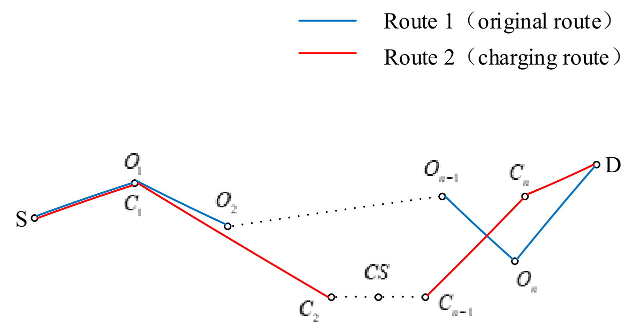

FIGURE 5. Original route and charging route.

C. TRAFFIC AND WEATHER INFORMATION

Daily load curve and curve of the congestion level is shown in figure 2. The peak period of load curve occurs from 9:00 to 22:00, when the traffic rush hours continues from 7:00 to 11:00 and 16:00 to 18:00 [34]. During traffic rush hours, EV users are more likely to use their EVs, so the fast charging load will also increase along with the increasing charging demand. Furthermore, the load of the power grid is also at a high level (peak load) during this period so that the fast charging demand will increase the peak load even further.

The temperature of a district will have a huge difference in different weather. Fig 3 shows the annul temperature and humidity of Wuhan. The most comfortable in-car temperature is between 19 degrees centigrade to 23 degrees centigrade. But the temperature of Wuhan can reach 40 degrees centigrade in summer when it can be as low as minus 10 degrees centigrade in winter. So, the energy cost of the air conditioner will be extremely high in summer and winter. Maintaining stable environment humidity is another basic function of air conditioners, research showed that it would be more comfortable if humidity is controlled under 60% [35]. So, controlling in-car humidity will also increase the energy cost of air conditioners.

Air conditioner is a basic part of EV, it is the second energy consuming component of EV, so the energy cost of it (C_A) is enormous, especially in extreme weather.

D. ENERGY COST MODEL

The energy cost can be divided into two parts as shown in figure 4: energy cost of EV engine (C_E) and EV air conditioner (C_A).C_E will be influenced by average speed (v) and distance (l), v is related to congestion levels of each road segments. C_A depends on the travel time of EV (T_r), waiting time of traffic signals (T_{ts}), queuing time in charging station (T_{cs}), humidity level (RH) and temperature (t).

So the total energy cost can be expressed as:

$$C_T = C_E(v, T_{ts}) + C_A(t, RH, T_R, T_{cs}, T_{ts}) \tag{1}$$

Route sketches are shown in figure 5. Route 1 is the original route, it goes through nodes S and D. Route 2 is the charging route, it goes through charging station CS. The extra energy cost of charging process (ΔC_T) is expressed as :

$$\Delta C_T = C_{TC} - C_{TO} \tag{2}$$

where C_{TC} and C_{TO} are the energy cost of charging route and original route respectively.

In cities, travel velocity will be limited on urban roads. Velocity's influence on energy cost is not significantly when EVs travel in low speed, so in this paper, velocity's influence is ignored, travel distance is the only element whose influence on C_E is considered. C_E can be express as:

$$C_E = \frac{l}{l_T} \cdot W_B \tag{3}$$

where l_T is the endurance mileage of EVs, W_B (kW ·h) is the battery capacity, l is the mileage of charging process.

As for the energy cost of the air conditioner C_A, the main influence factors are temperature and humidity In this paper

C_A is expressed as:

$$C_A = \int_{t_0}^{t_n} 1.1 \cdot [Q_{car}(t) + Q_n(t) + Q_h(t)]dt \tag{4}$$

where Q_{car} represents the power which is transferred into EV, Q_n represents the power which is brought by fresh air, Q_h represents the power to maintain the stable of humidity in the EVs. The margin index of this formula is 1.1. t_0, t_n represent the starting time and ending time respectively.

$$Q_{car}(t) = Q_g(t) + Q_{cr}(t) + Q_{cs}(t) + Q_{cub}(t) + Q_{ce}(t) + Q_p(t) \tag{5}$$

$$Q_n(t) = \frac{l_o \cdot n_p \cdot \rho_a \cdot \Delta H(t)}{3.6} \tag{6}$$

$$Q_h(t) = \frac{L \cdot \Delta H(t)}{V_a \cdot (1 + X)} \tag{7}$$

where Q_{car} represent the power transferred through glasses, roofs, sides, underbodies of EVs and passengers respectively, l_o is fresh air volume, n_p is number of passengers, ρ_a is air density, ΔH is enthalpy difference between in and out of EVs, L is fresh air volume of air conditioners, V_a is specific volume of air, X is absolute humidity.

$$Q_g(t) = k_{glass} \cdot S_{glass} \cdot [T_{out}(t) - T_{in}(t)] \tag{8}$$

$$Q_{cr}(t) = k \cdot S_{cr} \cdot [T_{out}(t) - T_{in}(t)] \tag{9}$$

$$Q_{cs}(t) = k \cdot S_{cs} \cdot [T_{out}(t) - T_{in}(t)] \tag{10}$$

$$Q_{cub}(t) = k \cdot S_{cub} \cdot [T_{out}(t) - T_{in}(t)] \tag{11}$$

where k_{glass} represents heat transfer coefficient of glasses and k represents heat transfer coefficient of car bodies. S_{glass}, S_{cr}, S_{cs}, S_{cub} represent the area of glasses, roofs, sides, underbodies of EVs, respectively. T_{out} is the temperature outside EVs and T_{in} is the temperature in the EVs.

E. QUEUE MODEL

The number of charging poles in each EVFCSs are limited, if EV users choose to charge at rush hours, they may well need to wait in lines. Queuing time in EVFCSs can affect the using time of air conditioners significantly. Therefore it will also affect C_A. So it is necessary to evaluate the queuing time.

In this paper, we regard the queue model as a $M/M/s/K$ model. That means arrival time and charging time of EV users subject to Poisson distribution, number of charging poles is s and the number of parking spaces for EVs to wait in line is K. In this paper, we express real-time arrival rate and service rate as $\lambda(t)$ and μ respectively. So the service intensity of the system can be expressed as:

$$\rho(t) = \frac{\lambda(t)}{\mu} \tag{12}$$

The system idle probability is expressed as:

$$p_0(t) = \frac{1}{1 + \sum_{n=1}^{K} \rho(t)^n} \tag{13}$$

The costumer loss rate is expressed as:

$$p_K(t) = \frac{\rho(t)^K}{s!s^{K-s}} \cdot p_0(t) \tag{14}$$

According to formulas (12) to (14), the average queuing time of EVs can be worked out as:

$$W_q(t) = \frac{L(t)}{\lambda(t)[1 - p_K(t)]} - \frac{1}{\mu} \tag{15}$$

where $L(t)$ is the real-time number of EVs in the EVFCS.

III. NAVIGATION STRATEGY

A. OBJECTIVE

The target of the HNS is to achieve the peak shaving of the load curve. So the objective is minimizing the extra energy cost of charging process, which can decrease the charging demand during peak periods:

$$\min \ C_E(v, T_{ts}) + C_A(t, RH, T_R, T_{cs}, T_{ts}) \tag{16}$$

The charging time selection layer and route selection layer of the proposed navigation strategy are formulated as follows. First, before the EV user starts the first trip of the day, charging time selection layer should recommend EV user an approximated time to charge according to the information of the EV user's using habit and battery's state of charge. This step can help to avoid charging in case that SOC is still at high a level. Then the optimal selection layer based on PCGA will propose the charging time slot and route to EV users, which can help to decrease the charging energy cost and extra time for charging.

B. CHARGING TIME SELECTION

EV users always not just use their EVs once a day, for example, the daily trip frequency of Wuhan citizens is 2.4 [36]. That's to say, EV users will have more than one chance to charge their EVs in a day. So they can choose to avoid charging their EVs in rush hours, thus can shave the peak load and decrease the time cost of EV users, at the same time it will not change EV users' daily travel habits, save their charging time cost and charging cost.

In this section, we proposed an optimal selection method to select charging time for EV users. The flow chart of the proposed strategy is shown in figure 6.

The first step is inputting the data of EV's daily average mileage and state of charge (SOC). Then, the system should judge whether the SOC of EV's battery is much than 30%. If it is much than 30% and can meet the demand of 2 days at the same time, EV users will be suggested to charge in another day, or the system should step to the next criteria. Then, if the SOC can meet the demand of 1day, the next step will be the optimal selection of charging time slot, or the EV user will be proposed to charge in the first charging time slot of the day. The rate of adoption is also considered to take EV users' extra demand into consideration.

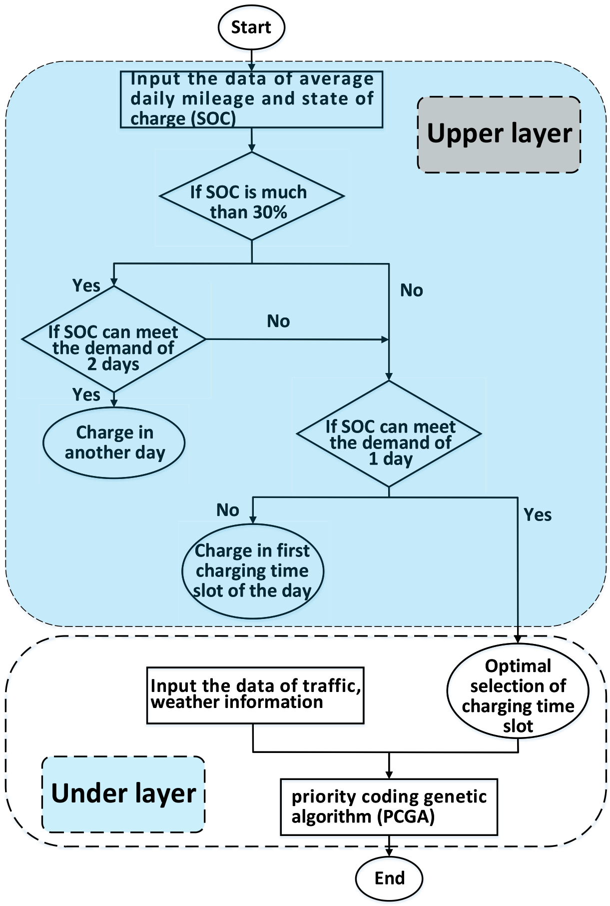

FIGURE 6. Flow chart of time selection.

A figure of the time slot W is provided according to EV users' using habit to describe possible charging time slots.

$$W(t) = \begin{cases} 1 & \text{able to charge} \\ 0 & \text{unable to charge} \end{cases} \tag{17}$$

If $W(t_k) = 1$, the EV user will be able to charge in t_k, otherwise the EV user will be unable to charge.

The constrains of charging time are as follows:

(1) The whole charging process should start and end at the time when the EV user can charge. At the same time, the charging process should be continuous, that is to say, any time between start time to end time should be able to charge for EV user.

$$W(t_s) = 1 \tag{18}$$

$$W(t_e) = 1 \tag{19}$$

$$W(t) = 1, \quad \forall t \in [t_s, t_e] \tag{20}$$

(2) The duration between the start time and the end time can be defined as Δt.

$$\Delta t = t_e - t_s \tag{21}$$

And there should at least exist one Δt to hold following inequation which is to maintain that the duration is enough for the whole charging process.

$$\Delta t \geq t_{original} + t_{charging}, \quad \exists \Delta t = t_e - t_s \tag{22}$$

where $t_{original}$ is the time cost of original routes and $t_{charging}$ is the time cost of charging process.

As for constrains of EVs' batteries, its SOC should be less than 30% according to the flow chart. At the same time, the SOC should be higher than 10%, because deep discharge can be harmful to EVs' batteries.

$$10\% \leq SOC \leq 30\% \tag{23}$$

C. ROUTE SELECTION

Route selection layer should start at the same time as the start of the charging time selection layer. The constraint about the route is that each node cannot be passed twice in a route of charging $R[n_1\ n_2 \ldots n_k]$.

$$n_i \neq n_j, \quad \forall i, j \in [1, n] \tag{24}$$

On the aspect of energy constraint, the energy cost during the charging process cannot be higher than the remaining capacity of batteries.

$$Q_t(t) = Q_{car}(t) + Q_n(t) + Q_h(t) \tag{25}$$

$$C_{Bn} = C_{B0} \cdot SOC \tag{26}$$

$$\frac{l}{l_T} \cdot W_B + \int_{t_s}^{t_e} 1.1 \cdot Q_t(t)dt \leq C_{Bn} \tag{27}$$

where $Q_t(t)$ is the total power of air conditioners and C_{Bn} is the remaining capacity of batteries.

To select charging time and routes, a model based on PCGA is provided in this paper. The flow chart of this model is shown in figure 7.

The PCGA is consist of the following four steps:

1) PRODUCE THE INITIAL POPULATION

The encoding style of routes is to assign priority values to all nodes. According to proposed traffic/weather information, we assign priority value 1~18 to the 18 nodes randomly. The arrays of priority value are regarded as individuals in the population. Then work out the routes of each individual and exclude the illegal individuals (unable to find out the routes through priority value) until the number of individuals reaches the presupposed population size (n_p). The procedure of this step is shown in figure 7. The information of start time is also coded in the gene of individuals.

2) CALCULATE THE FITNESS VALUE

The fitness in this paper is the energy cost of charging C, contains energy cost of engine C_E and energy cost of air conditioner C_A. The calculation method is proposed in section II.

3) SELECT AND DUPLICATE

The target of the method is minimizing the energy cost of charging, so we should select the individuals whose fitness

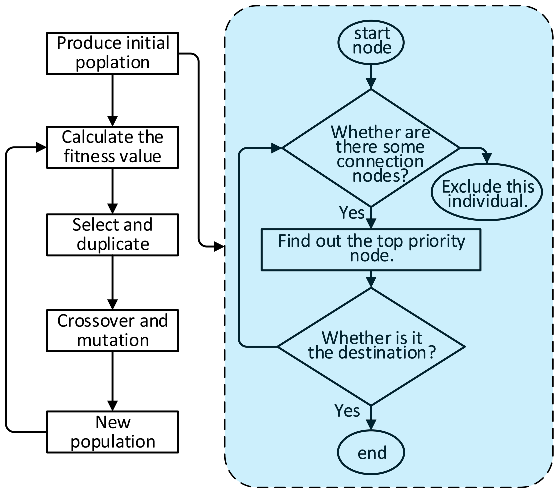

FIGURE 7. Flow chart of PCGA.

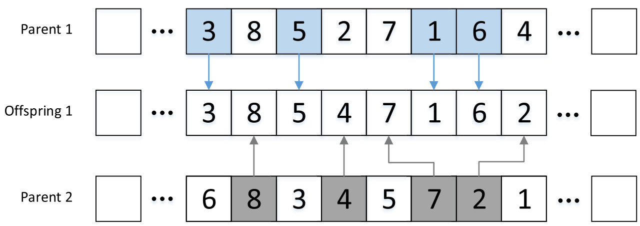

FIGURE 8. The procedure of crossover.

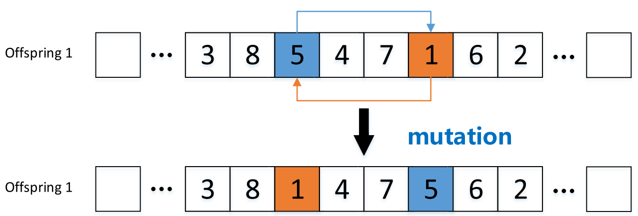

FIGURE 9. The procedure of mutation.

value are minimum. According to the fitness value, roulette wheel selection strategy is used to select and duplicate individuals who can let selection probability of individuals follow the distribution of fitness value.

4) CROSSOVER AND MUTATION

The procedure to get offspring is shown in figure 8. Crossover according to the crossover rate can produce new gene combinations and hope to combine the beneficial genes together. The basic content of mutation is to change the gene value of individual strings in a population. At first, select half of the genes from parent 1 randomly, put them into the same positions of offspring 1. Then find out other genes from parent 2, and put them into the rest positions of offspring 1 and 3 in order. At last, allocate the information about parents' start time to offspring 1 and 3 respectively. Offspring 2 and 4 can also be got through this way. The procedure of mutation is choosing two genes and change their position which is also shown in figure 9.

The integral process is shown in figure 10.

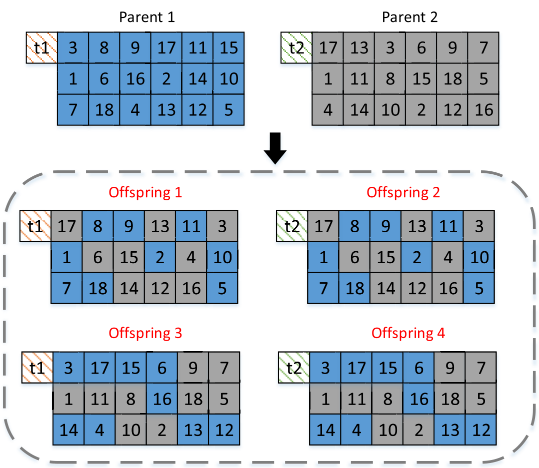

FIGURE 10. The integral process of crossover and mutation.

Then, put all the offspring created by duplication, crossover, mutation together, calculate their fitness value and find out n_p individuals with best fitness values.

IV. CASE STUDY

A. MODEL DESCRIPTION AND SETTINGS

In this paper, all the models are carried out through the Matlab platform. To verify the effectiveness of the proposed hierarchical navigation strategy (HNS), a model of shortest path algorithm (SPA) is built to compare with the HNS.

Simulation studies are performed based on the city map of Wuhan, Hubei, it is simulated based on the part of the map of Wuhan, Hubei. The traffic model is shown in figure 11 and model parameters are shown in table 1. It contains road segments, intersections and EVFCSs. Each road segments of it are main roads (two-way roads), so EVs can pass these roads from two directions. The congestion level of each road segments can change over time, and it will influence the travel time of EVs on the roads. Traffic signal lamps which can also influence time cost of EVs are located at nodes 3, 4, 7, 9, 13, 15, 16, 17, and three EVFCSs are located nearby nodes 8, 12, 14. According to the congestion levels and real velocity data [34], we set four velocities: 49km/h, 42km/h, 35km/h, 28km/h corresponding to four congestion levels. The average waiting time for signal lamps is 75 seconds. As for weather information, we choose the weathers of Wuhan for the case study. EV model of this paper is built according to BAIC MOTOR C50EB, whose battery capacity and driving mileage is 41.4kW·h and 220km respectively.

B. RESULTS AND ANALYSIS

In this paper, the results of the case study are worked out and analyzed at the following three aspects.

1) IMPACT ON CHARGING LOAD CURVE

Figures 12-13 show the fast charging load curves in summer and winter respectively. In summer, the charging load of

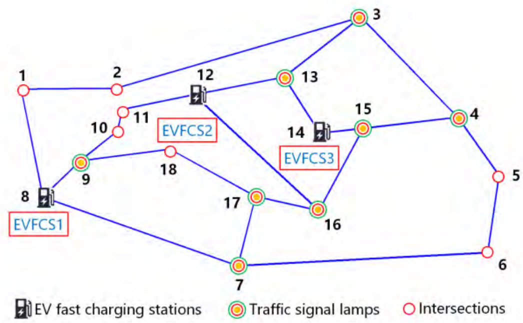

FIGURE 11. The traffic model based on Wuhan, Hubei.

TABLE 1. Model parameters.

traffic	congestion levels	unimpeded	slow	crowed	jammed
	average velocity	49km/h	42km/h	35km/h	28km/h
	traffic signals	Nodes 3, 4, 7, 9, 13, 15, 16, 17			
	EVFCSs	Nodes 8, 12,14			
	average waiting time(for traffic signals)	75 seconds			
weather		temperature		humidity	
	summer	28~38℃		43%~81%	
	winter	-9~3℃		45%~79%	
EV	type	BAIC MOTOR C50EB			
	battery capacity	41.4kW·h	driving mileage	220km	
	average daily trips	2.4	daily mileage	7.3km	
queue	charging poles(s)	8	parking spaces(K)	10	
	service rate(μ)	0.267			

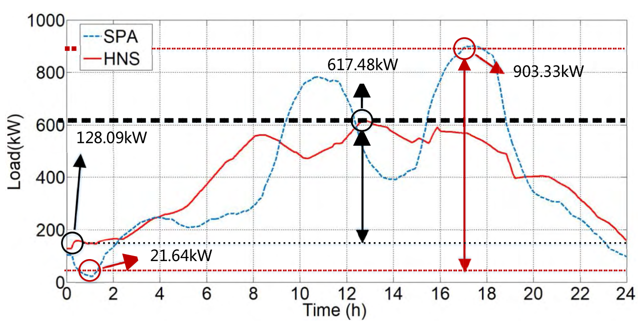

FIGURE 12. Fast charging load curves in summer.

the SPA reaches the highest point in about 5 pm, which is 903.33 kW. The line chart also shows that the bottom of the load curve of the SPA is 21.54 kW, which appears at midnight. So the difference between peak charging load and vale charging load is 881.79 kW when EV users following the SPA. On the other hand, the maximum and minimum

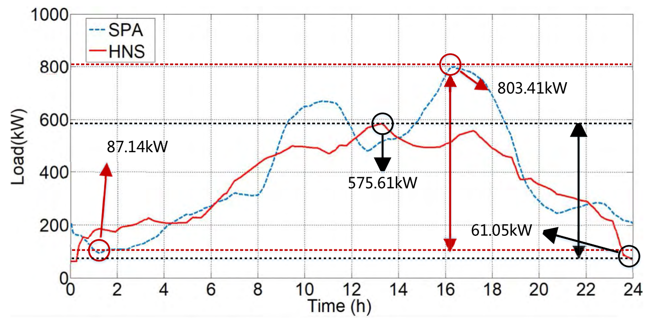

FIGURE 13. Fast charging load curves in winter.

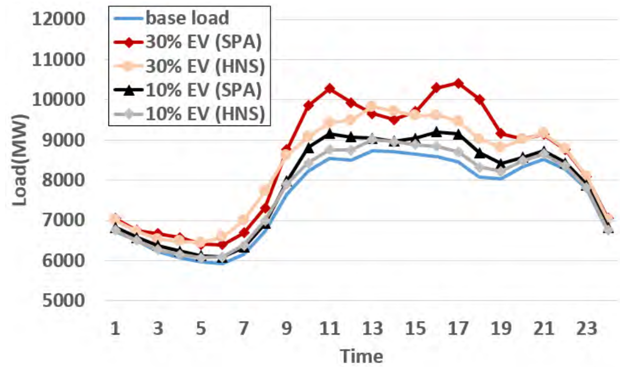

FIGURE 14. Load curves in summer.

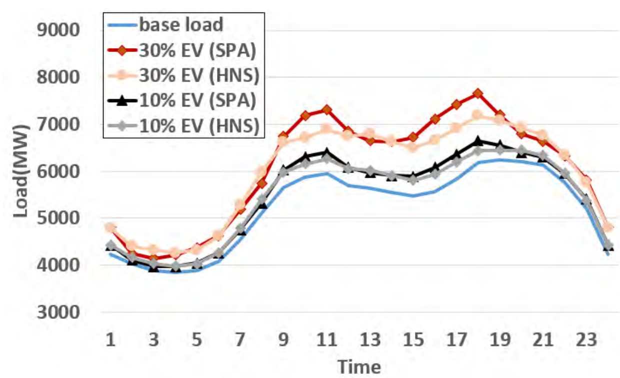

FIGURE 15. Load curves in winter.

values are 617.48 kW and 128.09 kW respectively when EV users following the HNS. The difference between them is 489.39 kW, which is about half of the case of the SPA. The charging load is lower than in summer as a whole in winter. In this scenario, the difference between the SPA and the HNS is still obvious. During 8 am to 11 am and 1 pm to 4 pm, the load curve of the SPA rises dramatically between 315.17 kW to 673.01 kW and 481.29 kW to 803.41 kW. At the same time, the load curve of the HNS keeps relatively stable from 8 am to 4 pm.

Comparing with the SPA, charging load curves of the HNS are smoother, fast charging load is lower in rush hours when it is higher in some hours of off-peak periods. Two possible causes can be concluded to explain the results: (1) charging

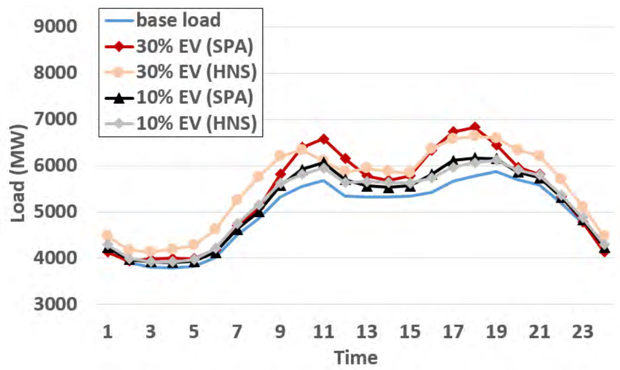

FIGURE 16. **Load curves in other times.**

TABLE 2. **Load reduction under the HNS compares to the SPA.**

	summer	winter	others
EV penetration:10%	2.01%	3.09%	0.79%
EV penetration:30%	5.65%	6.17%	2.84%

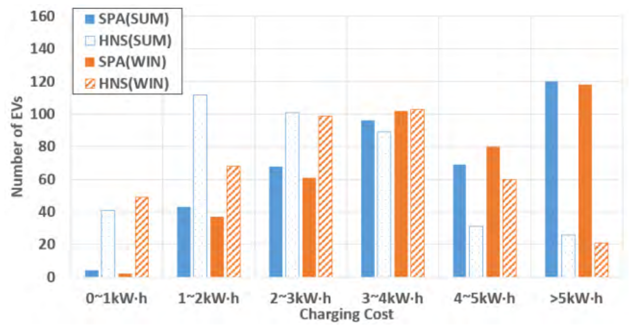

FIGURE 17. **Distribution of charging energy cost.**

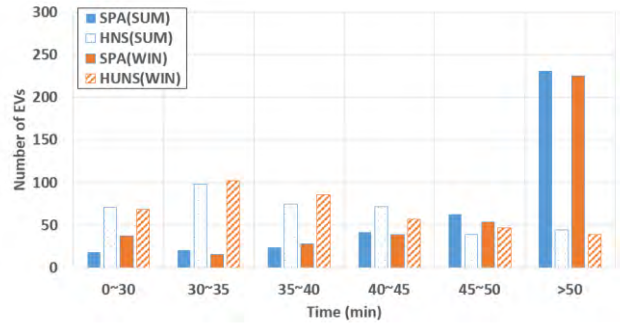

FIGURE 18. **Distribution of charging time cost.**

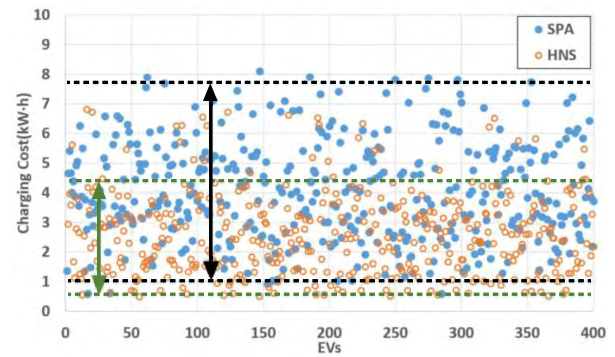

FIGURE 19. **Charging energy cost in summer.**

time selecting step of the HNS can help EV users choosing better time, thus reduce the possibility of charging at rush hours or charging in the case that SOC is still at high level (>25%); (2) route selecting step of the proposed HNS can offer better charging routes for EV users to reduce charging energy cost, thus will decrease the total charging demand especially in rush hours. So the results can demonstrate the validity of the HNS's peak-shaving function.

Figures 14-16 are worked out based on simulation results of fast charging load. They show the load curve of Wuhan power gird in case of different EV penetration. The basic load curves of Wuhan in summer and winter are obtained through the value of July/August and December/January in 2017. And the total amount of motor vehicles in Wuhan was about 2.7 million in 2017 [37]. Table 2 gives the information about the load reductions which are brought by the HNS to basic load in different scenes. If EV penetration is 10%, the peak loads of the SPA are 9199.25 and 6649.82 MW in summer and winter respectively when they are 9013.99 and 6444.21 MW in case of using the HNS. The reduction of peak load brought by the HNS is about 2.01% (summer) and 3.09% (winter). It can be seen that the difference of peak load between the SPA and the HNS is not significantly in occasion of low penetration. It is because the total load of fast charging demand in this occasion is far less than the base load, the proportion of reduction brought by the HNS is also low. In case of 30% penetration, the influence of EV fast charging to the power grid is far more obvious than in case of 10% penetration, the reduction of peak load brought by the HNS will increase to 5.65% (summer) and 6.17% (winter). Figure 16 shows the load curves in other time, whose temperature is not so extreme as in summer and winter. In this scene, the HNS can still bring improvements on load curve compare to the SPA, but the improvements are not as significant as in figure 14 and figure 15 due to the less energy cost of air conditioners in EVs.

2) IMPACT ON EV USERS' CHARGING COST

Figures 17-18 show the distribution of charging energy cost and extra time cost of all the samples (EVs). These figures illustrate that the HNS can reduce the EV charging cost. Figures 19-20 provide the statistics of the charging energy cost and time cost under two navigation strategies. The differences between the two strategies are most obvious in the intervals of more than 5 kW·h (energy cost) and more than 50 minutes (time cost). In figures 19-20, compared with the SPA, the charging energy cost of the HNS is distributed at the lower range. The average charging energy cost of the HNS is 2.61 kW·h and 2.84 kW·h in summer and winter respectively

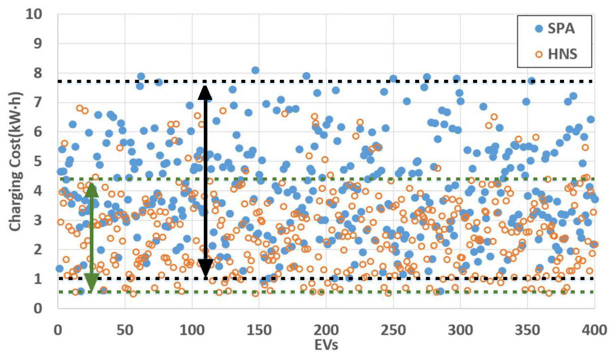

FIGURE 20. Charging energy cost in winter.

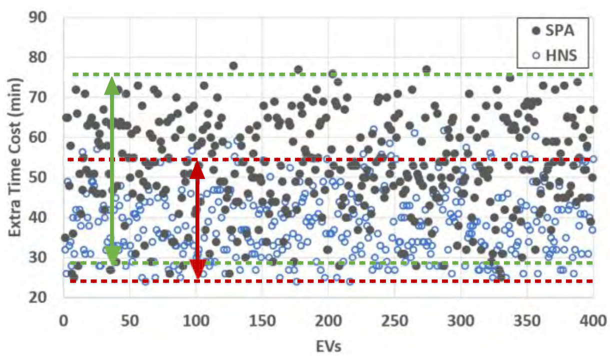

FIGURE 21. Charging time cost in summer.

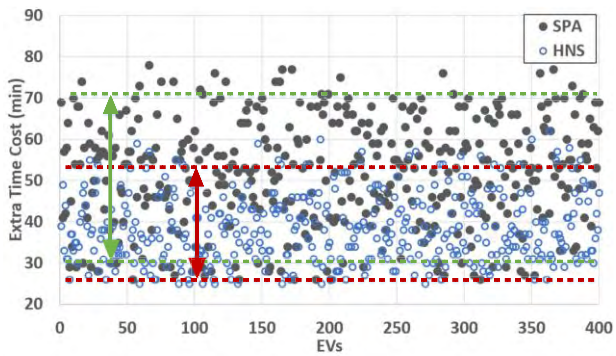

FIGURE 22. Charging time cost in winter.

when the value of the SPA is 4.06 kW·h and 4.17 kW·h. At the aspect of charging extra time cost, the distribution features are shown in figures 21-22, the charging extra time cost of the HNS is also distributed lower than the SPA. The average charging extra time cost of the HNS is 38.76 minutes and 36.33 minutes in summer and winter respectively when the values of the SPA are 52.78 minutes and 51.93 minutes. The results indicate that the HNS can help to decrease the charging energy cost and extra time cost significantly.

Table 3 shows some basic simulation results of the SPA and the HNS. Compared with the SPA, average start SOC of the HNS decreases by 20% due to the charging time selection step.

TABLE 3. Basic simulation results of the SPA and the HNS.

	SPA(SUM)	HNS(SUM)	SPA(WIN)	HNS(WIN)
Average start SOC	23.11%	19.06%	23.06%	19.45%
Average energy cost	4.17 kW·h	2.84 kW·h	4.06 kW·h	2.61 kW·h
Average time cost	52.78 min	38.76 min	51.93 min	36.33 min
Peak load	903.33 kW	617.48 kW	803.41 kW	575.61 kW
Bottom load	21.64 kW	128.09 kW	61.05 kW	87.14 kW

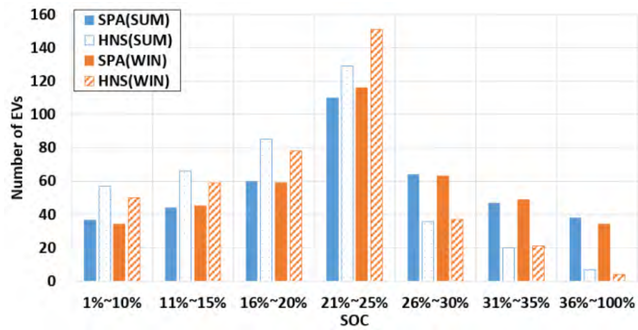

FIGURE 23. Distribution of initial SOC.

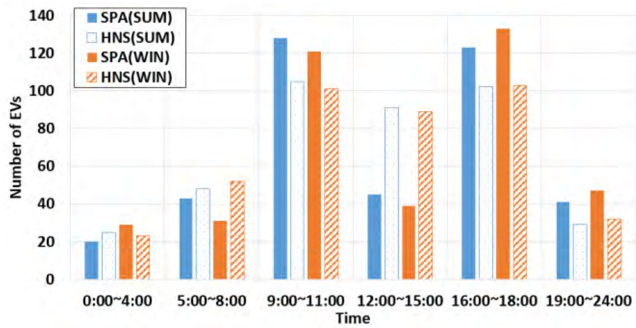

FIGURE 24. Distribution of the starting time.

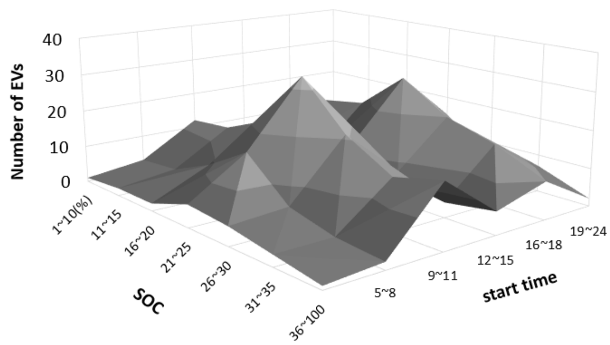

FIGURE 25. EV users' preferences (SPA, in summer).

3) IMPACT ON EV USERS' CHARGING CHOICES

At the aspect of EV users' charging choices, a statistical analysis comparing charging start time and initial SOC of two different strategies are carried out based on simulation results.

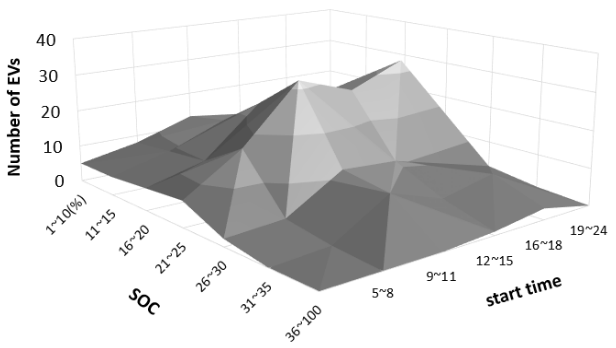

FIGURE 26. EV users' preferences (HNS, in summer).

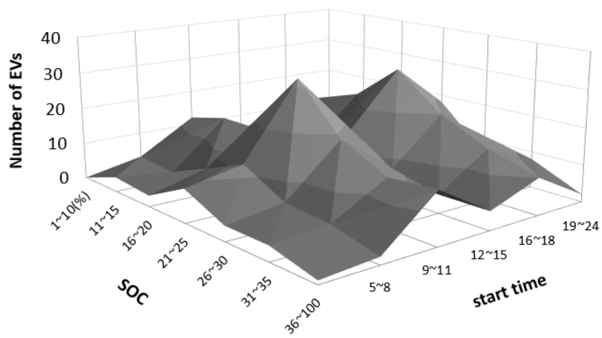

FIGURE 27. EV users' preferences (SPA, in winter).

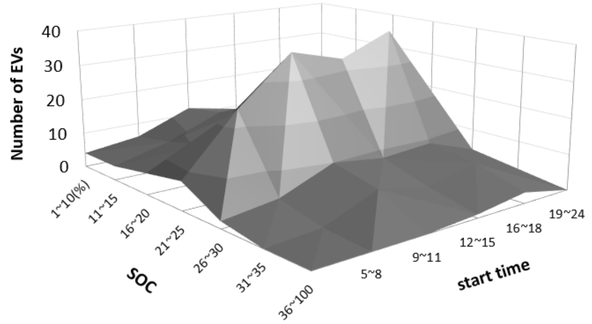

FIGURE 28. EV users' preferences (HNS, in winter).

Figures 23-28 give the information about the distribution of starting time and initial SOC in two different scenes: summer and winter. According to figure 23, the figures for the HNS are higher than figures for the SPA in the condition that SOC is lower than 25%. However, when it comes to the condition that SOC is higher than 25%, the result turns out to be the opposite. In figure 24, with the SPA, the number of EVs charge at rush hours (9:00∼11:00, 16:00∼18:00) is significantly higher than the figure for the HNS.

Figures 25-28 show the EV users' preferences of starting time and initial SOC under two strategies. When following the SPA, the starting time distribution concentrate at rush hours and initial SOC is normally distributed on a wide range. That means the majority of EV users tend to charge at rush hours, at the same time, many of them choose to charge when the SOC of their EVs is higher than 25%, which is still in high level. When following the HNS, more EV users choose to charge at off-peak hours and there are also many EV users decrease the initial SOC of charging.

V. CONCLUSION

This paper proposes a hierarchical navigation strategy (HNS) of EV fast charging. During the navigation process, dynamic traffic/temperature data and EV users using habits are considered. The proposed HNS first offers some efficient charging time slots according to EV users using habits, which can avoid charging at inefficient time slots. Then the HNS should select charging time from the candidate time slots to provide the optimal charging plan, at the same time, routes of the charging process should also be selected. A priority coding genetic algorithm (PCGA) is developed to solve the optimization problem. In this algorithm, priority codes are assigned to the nodes of the traffic system so that the routes can be worked out through the codes.

The case study of this paper is based on the traffic, temperature and power grid information of Wuhan, Hubei. Compares to the traditional shortest path algorithm, the proposed hierarchical navigation strategy can shave the peak load significantly, especially in the scenarios of high EV penetration and extreme weathers. At the same time, the energy and time cost of EV users can also decrease dramatically.

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