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Charging scheduling strategy for different electric vehicles with optimization for convenience of drivers, performance of transport system and distribution network

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A B S T R A C T

With the popularization of electric vehicles, large-scale electric vehicle charging may negatively impact drivers, the power grid, and traffic conditions. Currently, research conducted on the charging and battery swap of electric vehicles is insufficient. The objective for optimization and the type of electric vehicle proposed by other papers are limited in scope. In order to achieve an overall optimization of the whole system, the driver demands, the road traffic speed, the number of vehicles in the charging station and the charging network load are considered in the development of the charging scheduling strategy for electric vehicles. Such a strategy can further enhance driver convenience in terms of making decisions for charging and battery swap of electric vehicles. Moreover, different types of electric vehicles are taken into account for a more practical proposed scheduling strategy. Utilizing MATLAB and MATPOWER, a simulation platform is established to validate the strategy. Simulation results demonstrate that the proposed scheduling strategy can relieve local traffic jams, smooth network load curve, increase safety and economy of the power network, and decrease the number of charging electric vehicles in station. Ultimately, this plan can simultaneously reduce waiting time of charging and increase the operational efficiency of charging stations.

1. Introduction

With energy issue becomes more severe [1], Electric Vehicles (EVs) are becoming the ideal mode of transportation and receiving ever-increasing attention. Conventional vehicles inevitably contribute to an increase in carbon dioxide (CO_2) emissions, especially in large cities [2]. EVs possess significant potential in reducing CO_2 emissions [3]. In addition, EVs will be imperative to preserving traditional fuels and fully utilizing renewable sources. More specifically, a mass of electric vehicles can make use of the excess solar electricity generation at sun peak hours [4]. The authors in Ref. [5] described microgrid model including solar energy, wind energy and electric vehicles. Electric vehicles which have greatly increased efficiency represent an opportunity to transition from fossil fuels to tidal power [6]. As the major energy consumer and main contributor to carbon emissions [7], China places painstaking emphasis on the rapid development of electric vehicles [8].

Although EVs are becoming increasingly popular, a profusion of unsolved problems still remain. Most importantly, EVs possess relatively short driving range that is currently limited by insufficient battery technologies, which ultimately hinders their convenience and reliability. Secondly, few charging bases currently exist and are unevenly distributed [9]. Because there exists an uncertainty in the timing, location, and power demand of EV charging, the random process of EV charging could potentially weaken the reliability of the power system [10]. The authors in Ref. [11] proposed a way to estimate the EVs' possible states regarding their location, grid connection periods and the energy demand. The peak period of EV charging load differs according to season [12]. Electric vehicles and their charge characteristics are also varied.

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Additionally, the convergence of EVs at charging stations would instigate traffic congestion [13]. In conclusion, a rational charging schedule is necessary.

To resolve the aforementioned problems, research on path and station for EV charging has been conducted. Eisner et al. [14] set forth planned charging stations and paths based on current GPS according to location of stations and free piles. Artmeier et al. recommended the nearest station for EV according to its position [15]. Based on the objective of shortest (travel time) route, Liao et al. offered a plan for EV charging route [16]. According to the historical data and the forecast of road traffic conditions, Huber and Bogenberger proposed a charging strategy to minimize total trip time, that is, times for both driving and charging [17]. However, such researches only consider strategies centered on driver convenience.

Meanwhile, other papers discuss load optimization strategies for power network under V2G. Guille and Gross [18] provided a comprehensive solution for charging and discharging EVs under V2G by optimizing power network and customer income. Hu et al. focused on the management mechanism under V2G for EVs by taking into account driver demands, charging costs, and cable and transformer limitations [19]. From the perspective of considering the will and interests of owners, Parsons et al. aimed to develop V2G contract terms [20]. The authors in Ref. [21] evaluated power supply-demand, power quality and unbalance of power related to EV connection. Sundstrom and Binding proposed a solution to the scheduling of EVs in terms of the effects of charging on the power grid that seeks to mitigate the influences of charging and increase power quality [22]. The authors in Ref. [23] offered an adaptive charging strategy to optimize charging scheduling and reduce charging load, voltage class, 3-phase imbalance of power network, and capacity violation of transformers. Nevertheless, these studies only consider the operation of the power network.

Additionally, a simulation system for the charging and battery swap of EVs is generated from transportation and power network information [24]. Tan et al. proposed the path planning model for EVs that includes parameters such as battery capacity, charging time, shipping demand and electricity consumption and possibly reduce consumption of the power network [25]. However, the above papers only take into account the scheduling of a single EV and fail to consider the charging influences on traffic and the power network by convergence of EVs.

Leemput et al. discussed the influence of single direction charging on the network of a certain area, but only evaluated the charging effects of private EVs [26]. The authors in Ref. [27] explored the influence of different charging strategies on distribution networks. Nevertheless, it similarly only accounted for private EV charging. Benetti et al. [28] focused on the reduction of peak load of the private EV charging process. Clement-Nyns et al. [29] assumed that users only charge at home and performed statistical analysis according to driving times by selecting three periods of least traffic as potential times to undergo charging. Based on the data, it examined the trend of EV driving and electricity usage. However, such studies only considered quick or slow charging of private cars, where neither the realistic application of EVs nor the driving and charging influence of different EVs were considered.

To a certain degree, the above researches can enhance the level of convenience for EVs or reduce the high demand charging effects of EVs on transportation and power network. However, studies of charging scheduling only had a single objective for optimization and explored a single type of EV. During the charging scheduling, the study did not consider the consequences of driving and charging of clustering EVs, and lacked a well thought out consideration for the benefits and charging demand of EV users.

Shortcomings exist in the current research of charging. To counter these problems, this paper offers an innovative charging scheduling strategy. The strategy methodically considers the unfavorable factors of charging and enhances the convenience and performance of transportation, power network and charging stations. Moreover, various types of electric vehicles and their different characteristics are taken into consideration. The scheduling processes include private EVs, EV taxis and EV buses.

The structure of this paper adheres to the following sequence: Chapter 2 introduces the charging and battery swap process for EVs; Chapter 3 introduces the charging scheduling strategy of EV including multi-object optimization functions, constraint conditions and certain weight coefficients. Chapter 4 introduces battery swap strategy; Chapter 5 introduces simulation results; Chapter 6 concludes the paper.

2. Scheduling process for charging and battery swap

The paper presents the scheduling process for charging and battery swap of different EVs. Based on a series of steps, consisting of vehicle power demand and driver decision, the system will schedule charging and battery swap for EVs according to current operation of transportation and power network. The process is shown in Fig. 1.

2.1. Judging charging/battery swap demands

If the system detects that residual power cannot sustain regular driving, a decision regarding the demand of charging/battery swap is made. If the EV can drive normally, the system will continue to judge whether the remaining energy is sufficient to reach the destination. If yes, scheduling will quit. If not, scheduling assumes there exists a demand for charging/battery swap.

2.2. Driver decision making

The ability for the driver to make the final selection of the charging station is important. To ensure the benefit of drivers, the paper considers driver decision in the design strategy: 1. Driver prefers the path with least traffic jams or shortest driving times to station. 2. Driver prefers the option with least wait time for charging or battery swap. 3. Driver prefers the nearest station for power consumption. Therefore, the scheduler considers drive time to, wait time at, and driving distance to each station. For each option, the scheduler notes the wait time at each respective station.

For EVs requiring charging or battery swap, the scheduler enters driver decision making mode, which consists of two main steps: 1. Confirm whether the vehicle needs to charge/battery swap; 2. Choose the desired path. Firstly, the driver should judge whether the vehicle requires charging or battery swap based on vehicle conditions. If the driver has no need, the scheduler exits driver decision making mode. If the driver desires charging or battery swap, the scheduler enters scheduling mode. Once the system has completed calculating the available paths to each station and each respective wait time, the driver can make a final decision on which path to take. This way, the driver is given full authority and can make decisions according to the current situation.

During the decision making process, if the driver does not choose any path supplied by the system, the system cannot obtain the driver's intentions, including charging/battery swap decision, intended charging/battery swap station and intended path. Of course, the system cannot use these information to route charging paths for other vehicles. The travel information of this vehicle, such as speed, is known, which will be used in the traffic statistics of section 5.3.1.

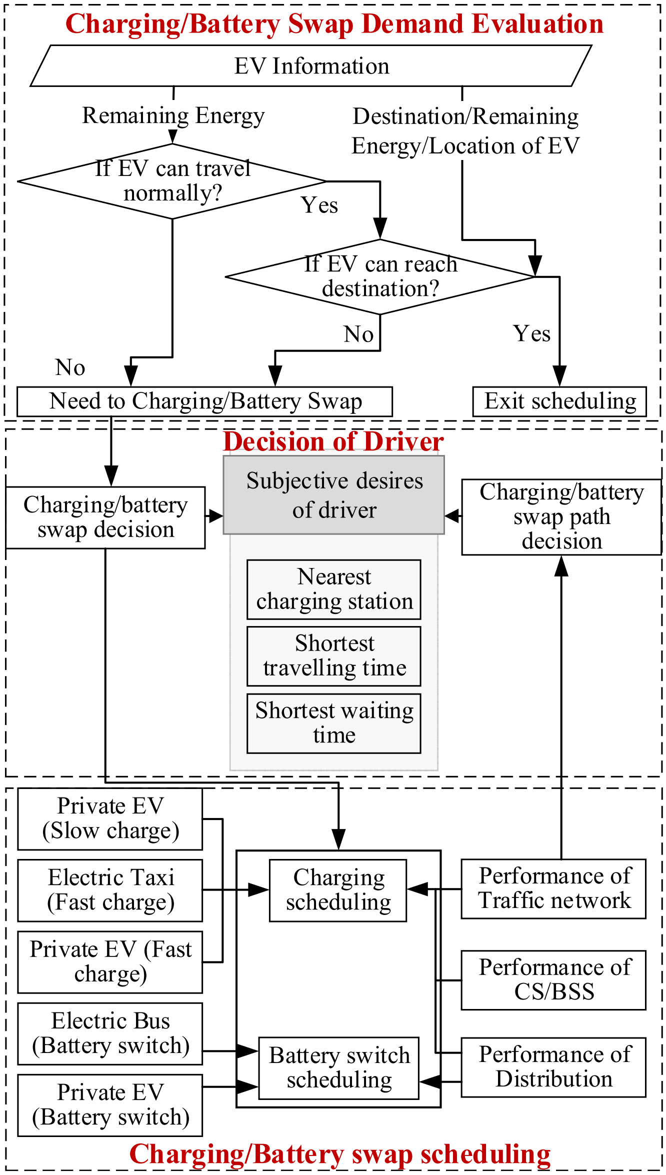

Fig. 1. Scheduling process for charging and battery swap.

2.3. Charging/battery swap scheduling

If the driver requires charging/battery swap, the system will plan the paths for different EVs according to current transportation and power network conditions. Then based on the driver input, the scheduler will update operation of the system to ensure real-time and accurate delivery of transportation and power network information.

2.3.1. Type of vehicles

Because driving and charging or battery swap of different types of EVs will influence transportation and power network to different extents, the paper offers a model based on the three parameters: $Type$, $Charge/Battery\_switch$ and $Travel$, expressed as (1).

$$EV = \{Type, Charge / Battery\_switch, Travel\} \quad (1)$$

a) Type

The paper classifies EVs based on usage and energy supply defined as follows:

$$Type = \{Function\_Type, Power\_Type\}. \quad (2)$$

According to different applications, EVs primarily include private vehicles, taxis and buses, which constitute *Function_Type*. According to electricity supply, EVs typically include quick or slow charging and battery swap, which constitute *Power_Type*. Considering EV applications in Beijing, this paper addresses charging and battery swap related to the following vehicle types: quick charging private vehicle, slow charging private vehicle, quick battery swap private vehicle, quick charging taxi, and quick battery swap bus.

b) Characteristic Parameters of Charging/Battery Swap

To accurately describe charging/battery swap, the paper chooses characteristic parameters, such as charging station (CS), time to charging station (CS_AT), waiting time (WT), charging time (Cha_T), charging power (P_Cha) and power consumption (P_Con). Thus, charging is defined as:

$$Charge = (CS, CS\_AT, WT, Cha\_T, P\_Cha, P\_Con) \quad (3)$$

Batter swap is similarly defined as:

$$Battery\_switch = (BSS, BSS\_AT, P\_Cha, P\_Con) \quad (4)$$

c) Driving

To accurately describe the driving information related to the transportation network, the paper defines initial position of EV (Dep), current position (Now), destination (Des), EV speed (V), path (*Path*), length of the path (*Path_l*) and mileage (*RemMile*) as characteristic parameters. Driving information is defined by the following formula:

$$Travel = (Dep, Now, Des, V, Path, Path\_L, RemMile) \quad (5)$$

2.3.2. Scheduling objects

During scheduling, according to real-time information from transportation, power network and charging stations, the scheduler plans the possible paths. Meanwhile, the information is also used to update system operation, which could provide the best choices for drivers. Overall, the whole process ensures optimization of EVs, transportation, power network and charging stations.

Because slow charging vehicles are able to utilize mains electricity, the paper only investigates quick charging private EVs, quick battery swap private EVs, quick charging taxi, and quick battery swap bus.

3. Charging scheduling strategy

Besides convenience, the strategy of this paper comprehensively considers the safe and efficient operation of traffic system, power network and charging stations. For path planning, the scheduler applies Dijkstra Algorithm [30]. Before path planning, road network was abstracted into a directed graph. When each road segment is given with the quantity and other physical significance, Dijkstra Algorithm can calculate charging path under different scenarios. The integral step in planning is to search for the path possessing the minimum weight value. Steps for charging scheduling are as follows:

1) Initialization. Scheduler initializes operation information of EV, power network, charging stations and transportation. Such information is used in measuring real-time operations of transportation, power network and charging stations. Additionally, it can be used to calculate the weight value during path searching.
2) Path planning for charging. As the initial step, the scheduler will judge whether EV with charging requirement is near any charging station:
   a) If yes, it will directly plan the path from the current position to the station;
   b) If not, it considers comprehensive weight values of transportation, power network and stations. Then, by Dijkstra Algorithm, it searches for the path with the minimum weight value.
3) Information update. It will carry out statistical analysis of the charging parameters and vehicle flow from different roads in order to update charging loads and vehicle quantity. Then it calculates the traffic speed for each road. After calculation is complete, it quits.

Path planning runs throughout the whole charging process and is highly dependent on the comprehensive weight value calculation results. Therefore, the key issue in this chapter focuses on the process of calculating the comprehensive weight value.

3.1. Object function

This paper researches the safe and efficient operation of transportation, power network and charging stations related to the charging scheduling for large scale EV applications, which introduces a typical multi-object optimization problem. The key to solving this type of multi-object problem is to build a reasonable objective function, which can ensure comprehensive optimization of the whole system.

A common method used in solving multi-object optimization problems is the Weight Coefficient Method [31]. However, the criteria of such a method is that each object function must possess the same dimensions. If this is not the case, the dimensionless method should be applied to the problem. Because the three optimization objects dealt in this paper have different dimensions, the dimensionless method must be employed for further analysis [32]. The dimensionless method applies a weighted summation of the three function objectives. The formulated function is expressed as equation (6).

$$F = w_1\frac{f1}{minf1} + w_2\frac{f2}{minf2} + w_3\frac{f3}{minf3} \tag{6}$$

Here$f1$,$f2$, $f3$are the velocity reciprocals of nearby roads, charging loads, and vehicle quantity in station respectively. min$f1$min$f2$,min$f3$ are optimal solutions that are computed by ignoring the other two optimization functions. $w1$,$w2$, $w3$ are weight coefficients for the three objects respectively. Details describing the three objects will be provided in latter sections.

3.1.1. Traffic side

To ensure optimal traffic operation, the paper calculates speed of roads. For one available road $(p,q)\in A$, where p and q are two adjacent nodes of a road section and A refers to a set of all roads in the whole area, the speed is defined as $V\{p,q\}(j)$ that originates from the flow at the end of the previous period $Q\{p,q\}(j-1)$. The classic Velocity-flow modeling [33] is given as equation (7).

$$V\{p,q\}(j) = \frac{V_m\{p,q\}}{1+Q\{p,q\}(j-1)/C\{p,q\}} \tag{7}$$

Road ability is defined as $C\{p,q\}$and Zero velocity as $V_m\{p,q\}$. They are built-in attributes of the road whose values are known. In order to ensure increased traffic performance, velocity of roads should be as high as possible; that is their reciprocals should be as low as possible, shown as equation (8).

$$f1 = 1/V\{p,q\}(j) \tag{8}$$

3.1.2. Power network side

As operation is related to network flow, limit charging load of stations will enhance the network operation. Load formula is shown as equation (9),

$$f2 = Load\_Charging(r, t_0) \tag{9}$$

where $t0$ is the estimated arrival time to Station$r$for EV.

3.1.3. Charging station side

When EVs cluster at a single station, wait times consequently increase. To avoid long wait times, the quantity of EVs at a single station should be restricted. Taking the charging station r for example, the system knows which vehicles select station r for charging/battery swap and the estimated arrival time to r for each EV. Therefore, it is easy to calculate the quantity of EVs in station r at different times, expressed as equation (10).

$$f3 = Num\_Charging(r, t_0) \tag{10}$$

Furthermore, charging power of each vehicle *P_Cha* is known for the system. Based on the quantity of EVs in station r and *P_Cha* of each EV, the charging load of station r can be calculated. This is the specific calculation process of equation (9).

For above objects, the charging scheduling strategy in this paper for large scale application will direct EVs to roads with higher speed and the station with less charging loads and less quantity of EVs.

3.2. Calculation of weight coefficient for object function based on fuzzy logic

Calculating the weight coefficient is the key issue for multi-object optimization. In this paper, fuzzy logic is applied to calculate the weight coefficient of function objects due to the uncertainty existing between the three objects and stochastic nature of the driving status of EVs.

The calculation process is shown in Fig. 2, where the system includes five parts consisting of input, output, fuzzy, derivation and defuzzification. The three factors, velocity of road, charging loads and vehicle quantity at station, are defined as inputs for fuzzy logic. The outputs are weight coefficients related to traffic network, power network and stations respectively. Using fuzzy method based

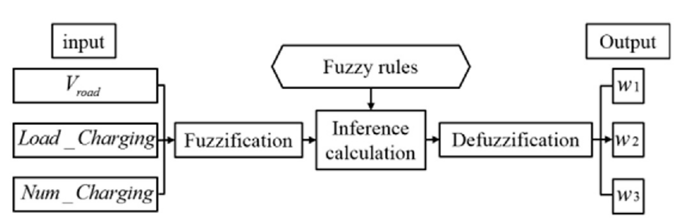

Fig. 2. Basic elements and topology of the road network.

on the inputs into the system and a set of fuzzy rules, the system calculates and defuzzifies to obtain the outputs. Fuzzy process and rules are the important elements in the overall calculation.

The system fuzzifies velocity of roads into three assemblies: Low velocity (L), Medium velocity (M), High velocity (H) Likewise, it fuzzifies charging loads into four assemblies: Low loads (L), Medium loads (M), High loads (H), Extra high loads (EH). Finally, it fuzzifies vehicle quantity into three fuzzy assemblies: Small (S), Medium (M), Big (B). Because overly excessive loads placed on the power network will result in a dangerous operation at power network side, high loads could potentially generate safety problems. Therefore, situations where high loads are present should be carefully monitored and prevented. In this paper, the membership function is dependent on a large amount of simulation results. Membership functions for different types of EVs should be separately confirmed.

Fuzzy rules are as follows:

1) If an exceedingly high load occurs, more priority should be given to the power network than the other two objects in order to assure safe operation of the power network.
2) If charging load is not excessively high and velocity is low, more weight should be placed on road traffic and less on the other two objects to guarantee traffic efficiency.
3) If loads are not exceedingly high and velocity is not low, values should be set according to an averaged approach.

3.3. Constraints

In order to ensure the rationality of the scheduling strategy, constraints on several aspects are established.

3.3.1. Road passage

To prevent congestion near the charging station at rush hour, the paper proposes the following rule: when the road congestion ratio reaches severe congestion, the roads within a 1 km radius of the charging station are closed to traffic. During these times, only the buses and other vehicles whose destinations are located in these areas, are allowed to pass, otherwise, not allowed. When the road congestion is not severe, all vehicles are permitted to enter. The mathematical expression is shown in (11), where a is the flag of whether the road is open to all vehicles. $a = \infty$ indicates being closed to traffic.

$$\text{if} \quad V\{p,q\} < 30\% \times V_m\{p,q\}, \qquad \text{then} \quad a(p,q) = \infty \tag{11}$$

3.3.2. Charging of electric vehicles

For rationality, the charging strategy of this paper targets EVs whose remaining range is no more than N% of maximum range, or residual distance is insufficient to reach the destination.

$$RemMile(i) \leq N\% \cdot Mile\_ful(i) \tag{12}$$

$$RemMile(i) \leq Path\_Length(i) \tag{13}$$

$RemMile(i)$ is the remaining range for EVi. $Mile\_ful(i)$ is maximum range of EVi. $Path\_Length(i)$ is the distance to the destination.

3.3.3. Mileage available for electric vehicle

For rationality, stations of plan should be within the remaining range of EV. If exceeded, the scheduler chooses the nearest station for charging.

$$RemMile(i) \geq Path\_L(i) \tag{14}$$

$Path\_L(i)$ is the distance to planned stations for EV i .

3.3.4. Station loads

According to charging requirement of EV users, the system should set a reasonable threshold of the station load.

$$Load\_Charging(r, t0) < P\_Limit(r) \tag{15}$$

$P\_Limit(r)$ is the threshold for Station r.

3.3.5. Operation of power network

To ensure safe operation of power network, before scheduling, the system should evaluate the economic feasibility and safety of power network at available stations. That is, it should estimate network loss and voltage deviation in order to avoid any decisions that would exceed the threshold value.

a) Network loss

With regards to certain load, connecting position, and capacity of stations, loss is mainly related to node load *Load_Charging*. Meanwhile, according to Network Performance Evaluation Standards [13] in a previous research, the power loss should meet the constraint, expressed as equation (16).

$$Ploss(Load\_Charging(r, t0), t_0) < 7\% \tag{16}$$

b) Voltage deviation for node

According to national standards, the distribution network within 20 kV should have a deviation ratio within ±7% [34]. The expression is as follows:

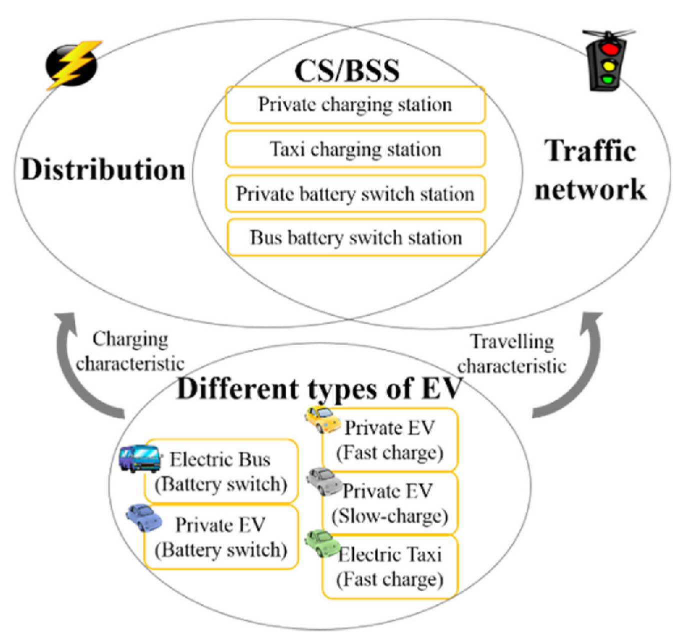

Fig. 3. Simulation System for charging and battery swap scheduling.

$$Vshift(Load\_Charging(r, t0), t_0) < 7\%. \quad (17)$$

4. Battery swap scheduling strategy

Other than the charging process, the paper provides a brief introduction to the battery swap process for EVs, which only applies to real-time scheduling for driving. For the battery swap process, the system enters offline scheduling. It assumes that battery swap stations have sufficient battery reserves, so vehicles can replace the battery in time without any associated charging wait time.

For driving scheduling, the system applies the path with the shortest drive time. This means that a weight value associated with drive time is chosen for the path. During the route selection process, the road traffic and accessible path constraints, represented from Eq. (11) to Eq. (14), must be satisfied. For scheduling of replaced batteries, the paper chooses power network connected by stations as the research object. With a reasonable optimization function, the system optimizes charging time and power consumption for replaced batteries at station based on current loads. In the subject preliminary research process, the aim is to smoothen loads on the power network for the orderly implementation of battery swap. The two objective functions are based on minimum standard deviation of loads and minimum load difference between peak and valley [13]. The method can potentially further even out distributions and enhance operations of the power network. However, the paper will not introduce this method in detail.

5. Simulation and analysis

To validate the strategy of this paper, this chapter builds up a simulation system for validation based on MATLAB.

5.1. Simulation platform

Based on MATLAB and MATPOWER, this chapter builds up a simulation system for the large application requirements of EVs. The simulation platform can simulate driving and charging behavior of electric vehicles, while updating the information of each model in real time. Fig. 3 illustrates the relationship between each part of the scheduling process. When an electric vehicle requires charging or battery swap, the electric vehicle needs to drive to charging station or battery swap station. Driving characteristic of electric vehicles contact with electric vehicles and traffic network. Additionally, charging characteristics cause the electric vehicles to be closely related to the power grid. The location of the charging stations is linked to the road transportation network and power grid.

In the early phase of this research [35], the transportation model was built up to include road scale, road level, length, maximum speed and road ability based on the realistic conditions up to the third ring of Beijing as demonstrated in Fig. 4. It introduces the traffic network in matrix form shown below in (18).

$$Map = \{Node, Connection, Grade, Velocity, Cap\} \quad (18)$$

A power network model with topology structure, capacity and impedance is established as shown in Fig. 5. The paper applies matrix (19) to the model:

$$Grid = \{Node, Branch, Generator\}. \quad (19)$$

*Node*defines the parameters as type, power and voltage for each

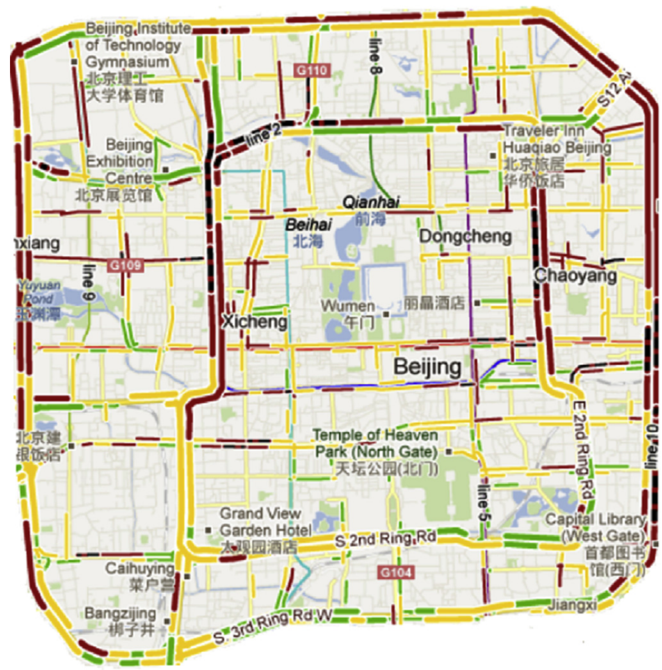

Fig. 4. Sketch map within Beijing tricyclic road.

node;*Branch* defines the connections and resistances for subbranches of nodes; *Generator*for source node defines the location and capacity of the power supply node. The simulation builds up 9 power networks covering the third ring of Beijing.

This paper builds up different simulation systems based on power network and traffic network models that consider charging and batter swap in different types of EVs and driving features. This part introduces modeling of EVs and charging stations.

5.1.1. Electric vehicle model

For private EV and taxi, power consumption per kilometer is around 0.15–0.2 kWh. For buses, it is around 0.8–1.2 kWh with higher power consumption.

For quick charging vehicles, the charging time is relatively shorter and consequently demands a larger charging power within the range of 25–60 kW. For battery swap, displaced batteries need a flattening power between the range of 2~4 kW.

5.1.2. Station model

Features such as location and power supply of stations connect EVs, power and traffic networks together. The paper models the location and power supply of stations related to the charging and battery swap station for private EVs, charging station for taxi, and battery swap station for bus.

5.1.2.1. Location of charging and battery swap stations. Since stations serve as a medium for traffic and power networks, locations are important for reasonable layout in traffic and power networks.

To create a reasonable layout of stations within the city, this paper generates a distribution for charging and battery swap stations, shown in Fig. 6. The diamonds, circles, triangles, and squares represent private EV charging stations (private CS), taxi charging stations (taxi CS), battery swap stations of private EV (private BSS), and batter swap stations of bus (bus BSS) respectively. The layout of stations is mainly based on investigation and reasonable assumptions relating to the actual distribution of existing charging stations

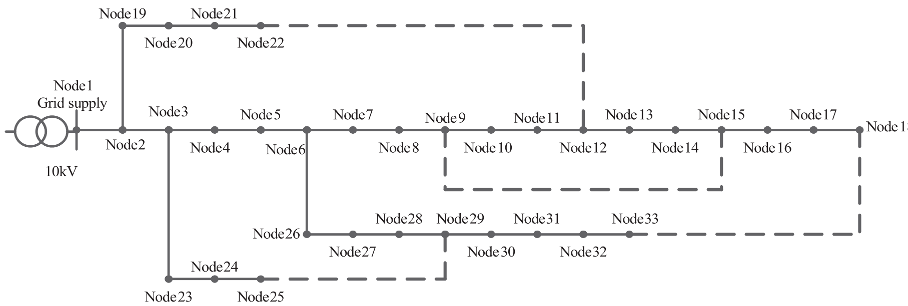

Fig. 5. Distribution model.

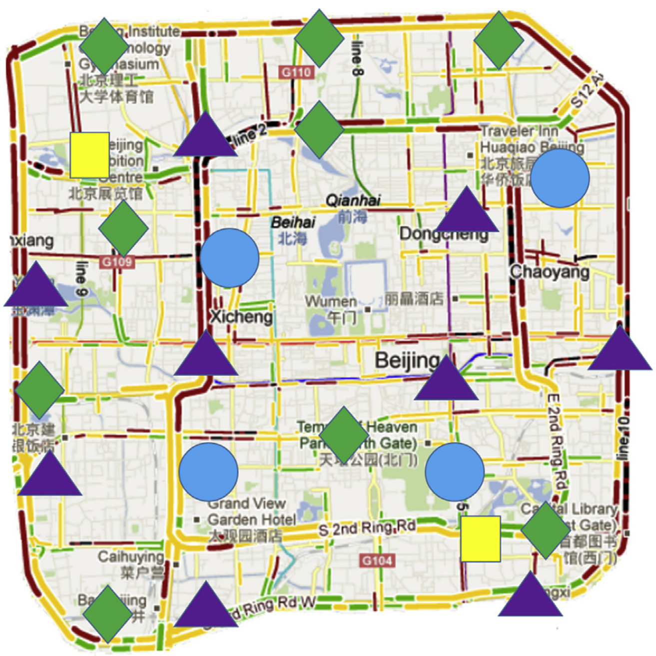

Fig. 6. Locations of charging and battery swap stations.

and bus stations in Beijing.

Layout of stations within the power network is shown in Table 1.

5.1.2.2. Power supply of stations. To introduce the power supply of stations, this paper chooses parameters such as station capacity (Cap), charging threshold (P_Limit), charging load (Load_Charging) and quantity for charging EVs (Num_Charging).

The paper sets reasonable capacity and charging load thresholds according to realistic power loads experience by stations in the area. The information of private EVs stations is shown in Table 2. Similarly, Table 3 is of EV Taxi stations.

Table 1
Relationship between stations and power network.

Distribution	Private CS	Private BSS	Bus BSS	Taxi CS
1	1	1	1	1
2	2	2	2	2
3	3	3		3
4	4	4		4
5	5	5		
6	6	6		
7	7	7		
8	8	8		
9	9	9		

Table 2
Station information for private EVs.

Private CS	Cap	P_Limit		
		Valley	Common	Peak
1	500	0.05	4.06	8.8
2	500	0.075	4.35	10.8
3	500	0.075	4.35	10.8
4	500	0.05	4.06	9.6
5	500	0.05	4.06	9.6
6	500	0.05	4.205	10.4
7	500	0.08	4.35	10.8
8	500	0.08	4.35	10.8
9	500	0.09	4.495	11.2

Table 3
Station information for EV taxi.

Private CS	Cap	P_Limit_CS		
		Valley	Common	Peak
1	80	1	2.2	2.5
2	80	1	2.2	2.5
3	80	2.3	3.2	3.8
4	80	2.3	3.2	3.2

5.2. Simulation design

For the charging scheduling strategy, a simulation scheme is designed, including simulation scale, weight coefficient and the comparative solution.

5.2.1. Scale design

Based on the simulation system introduced in Chapter 3.1 and the real traffic status in Beijing, the paper conducts a 24-h simulation. According to the distribution of residents' travel time recorded in the "Beijing Traffic Development Annual Report", different quantity of EVs are imported into the system every 5 min during different periods. Table 4 lists the quantity introduced

Table 4
Quantity of EVs for different periods.

Periods	Quantity introduced (per 5 min)
7:00–9:00	2300
9:00–17:30	900
17:30–19:30	2300
19:30–23:00	900
23:00–7:00	30

Table 5
Quantity for different types of EVs introduced.

Types	Quantity introduced (within 24 h)
Private EV (quick charge)	121,840
Private EV (quick battery swap)	80,000
Private EV (slow charge)	10,000
Taxi	30,000
Bus	1040

during different periods, where the total number of EVs amount to 242,880. The quantity of different types of EVs is shown in Table 5.

On the basis of actual traffic flow, all EVs are imported into the simulation system with their initial positions and destinations randomly assigned. It is assumed that initial SoC (state of charge) of each EV is randomly distributed between 5% and 100%.

5.2.2. wt coefficients

The calculation of weight coefficients is based on fuzzy logic. Membership functions are the important elements. Based on previous simulation results, membership functions are determined by an empirical method. To ensure simple practicality of fuzzy reasoning process and a better result of the proposed method, the membership functions adopt the triangle membership function and trapezoidal membership function. The eigenvalues of the traffic side were determined by counting the traffic speed under different weight coefficients. The average traffic speed during rush hours, usual hours and night time are the eigenvalues of the “H", “M" and “L". According to simulation conditions, when charging load is over 20 MW, the operation of power grid will be affected. When charging load reaches 23 MW, all grids will become dangerous. 20 MW and 23 MW are set as the critical value of “EH". “H", “M" and “L" are determined by average load according to the different times, which is similar to the traffic side. The membership function of the charging station side is based on the capacity of charging stations. 30%, 50%, and 70% of the capacity are taken as eigenvalues of “S", “M" and “B". Fig. 7 shows the membership function of the input variable for private EVs.

Fig. 8 shows membership functions of output variable for private EVs. Due to weighting coefficients of traffic side and charging station side containing three levels, 0.3, 0.5and 0.7 are set as characteristic value. Charging load weight includes four levels, so 0.2, 0.4, 0.6 and 0.8 are set as characteristic values.

According to the basic rules in section 3.2, 36 fuzzy rules are established. The representative fuzzy rules are as follows:

(1) If speed is L, charging load is EH and number of EVs is M, then w1 is L, w2 is EH, and w3 is L.
(2) If speed is L, charging load is H and number of EVs is B, then w1 is H, w2 is L, and w3 is L.
(3) If speed is M, charging load is M and number of EVs is M, then w1 is M, w2 is M, and w3 is M.

5.2.3. Comparison for simulations

In order to validate the strategy of charging, comparative simulation solutions are designed. For charging scheduling, traditional charging strategy is chosen for comparison purposes. The traditional charging strategy recommends the station nearest the current EV.

This paper focuses on comprehensive optimization of the whole system. In the simulation of the proposed strategy, the system selects the final charging route for each vehicle primarily according to equation (6). If the remaining range of the vehicle cannot meet the requirements for the planned path, the system will search for the nearest charging station.

5.3. Simulation result and discussion

The paper analyzes the result in three aspects: transportation, power network, stations and drivers.

5.3.1. Traffic side

Charging paths of electric vehicles directly impact operation of the traffic. During rush hour, the congestion is exacerbated in the city and charging of electric vehicles will aggravate traffic congestion around charging infrastructures. In order to ensure all charging vehicles arrive at charging station during the traffic peak time in a timely manner, a method to reduce congestion and improve traffic flow is needed.

5.3.1.1. Traffic congestion. Congestion ratio [13] is used to evaluate the condition of the road network. Congestion rate is the ratio of the number of congested roads to the number of selected roads. The heavy congestion ratios of fast charging stations nearby during rush hour are shown in Fig. 9 and Fig. 10. As shown, the maximum severe congestion rate of the optimized charging strategy is only 1%, and there is no severe congestion the majority of the time. Contrarily, the average severe congestion rate is greater than or equal to 4.0%, and the maximum rate is 8.3% using the traditional charging strategy.

5.3.1.2. Road speed. Fig. 11 and Fig. 12 show the traffic speed around NO.4 private charging station at rush hour in the morning, and NO.5 private charging station at rush hour in the afternoon respectively. The base speed is defined as the average road traffic speed when electric vehicle is absent. At rush hour, due to large charging demands, traffic speed in the vicinity of charging stations is bound to decline. As shown, the optimized charging strategy can sustain noticeably smoother traffic running conditions.

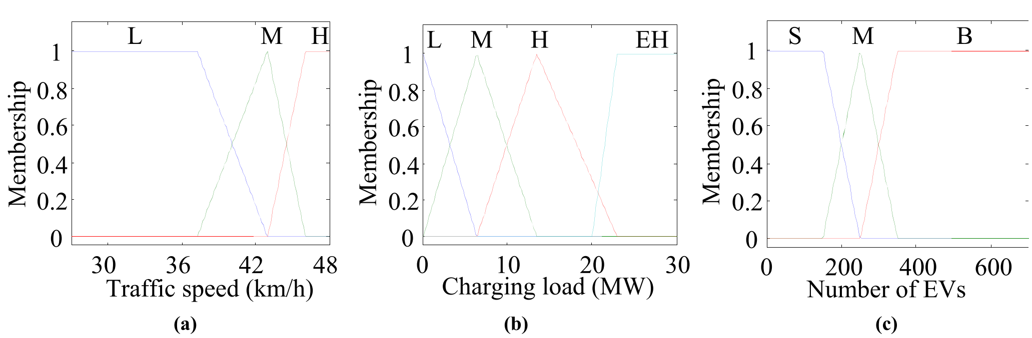

Fig. 7. Membership function of input on weight of (a) traffic, (b) distribution and (c) charging station.

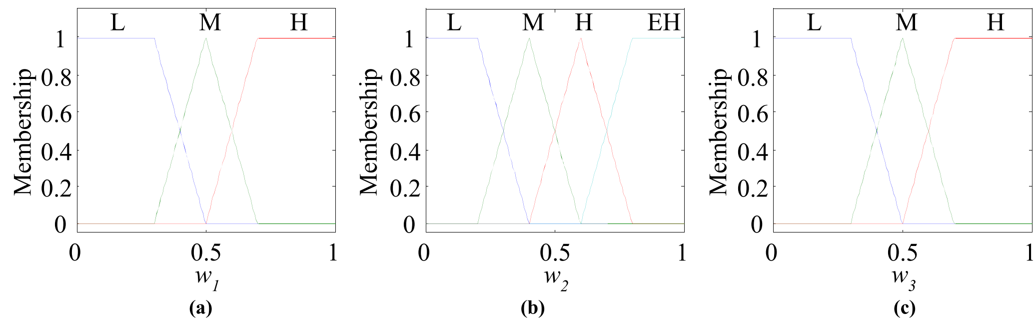

Fig. 8. Membership function of output on weight of (a) traffic, (b) distribution and (c) charging station.

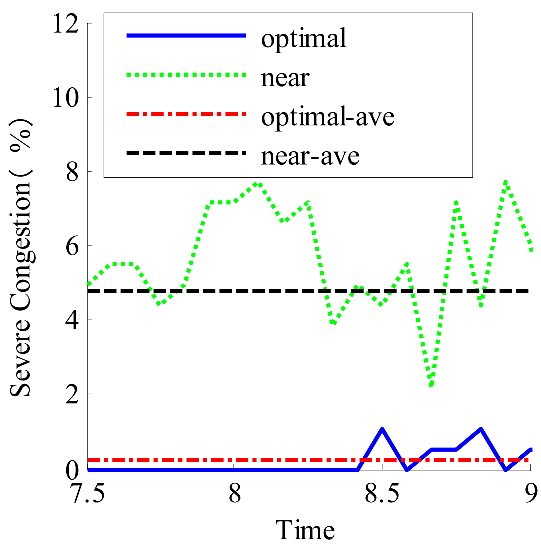

Fig. 9. Heavy congestion ratio of fast charging station during morning rush-hour.

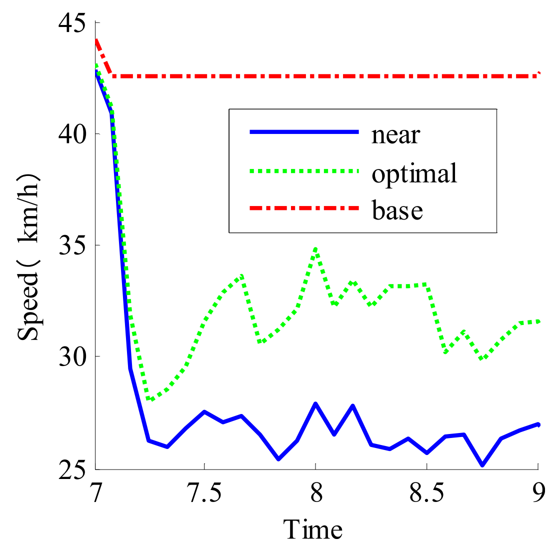

Fig. 11. Travelling velocity around NO.4 private charging station.

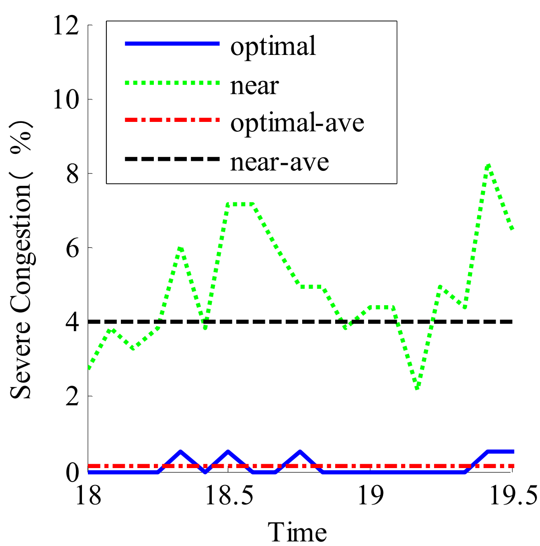

Fig. 10. Heavy congestion ratio of fast charging station during evening rush-hour.

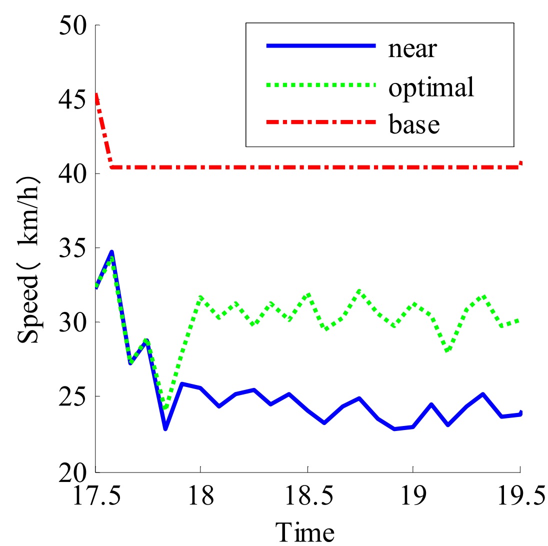

Fig. 12. Travelling velocity around NO.5 private charging station.

5.3.2. Power network side

5.3.2.1. Load distribution of stations. Fig. 13 and Fig. 14 illustrate the temporal and spatial distributions of the charging load for the two scheduling strategies.

Fig. 13 shows charging load of each private EV stations. Based on the traditional charging strategy, the load difference between each charging station is relatively larger. On the other hand, optimized charging strategy distribution of each station is more even, potentially benefitting the operation of power network and stations.

Fig. 14 (a) and (b) show that the load distribution with optimized

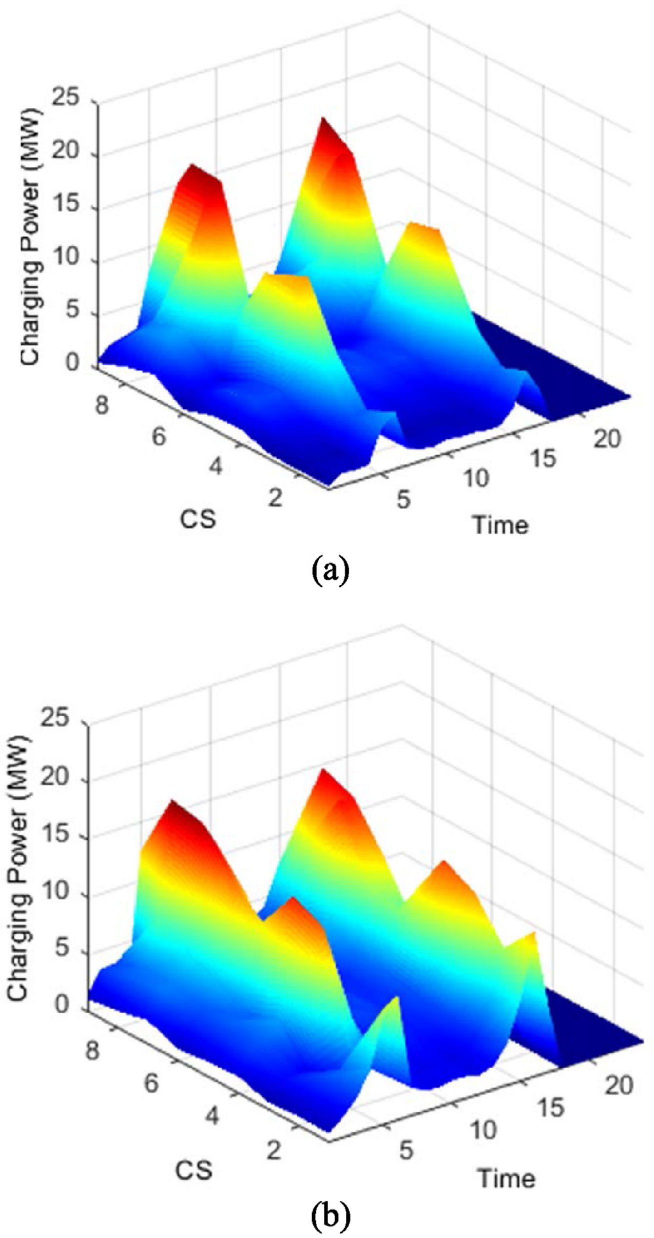

Fig. 13. Load distribution for private EVs: (a) the traditional strategy (b) optimized strategy.

strategy is further improved at stations for EV taxi. In the figure, CS stands for charging station for EV taxi and 1–4 represent numbers of charging station.

5.3.2.2. Analysis on power network. According to the load status for one day, the average power loss rate and maximum voltage deviation rate for that day is taken.

As shown in Fig. 15 and Fig. 16, higher loss rates and deviation rates of network 4, Network 7 and Network 8 are experienced when employing the traditional strategy. However, with the comprehensive optimization strategy set forth in this paper, the three networks show lower rates in terms of loss and deviation.

5.3.3. Charging station and driver side

5.3.3.1. Quantity of vehicles at station. Fig. 17 and Fig. 18 display quantity for station of private EVs and electric taxis with different

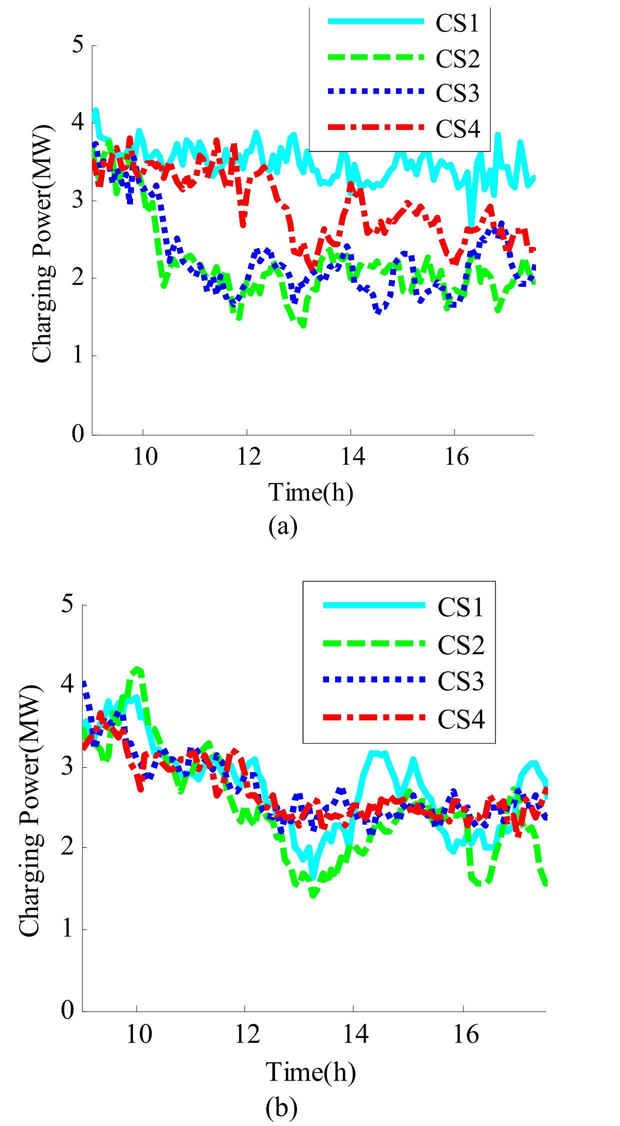

Fig. 14. Load distribution for EV taxi: (a) the traditional strategy (b) optimized strategy.

charging strategies.

Fig. 17 shows that Station 7 and Station 8 have the largest quantity of EVs for charging, while Station 2 has the least quantity of EVs when following the traditional strategy. The comprehensive optimization strategy decreases quantity of private EVs at Station 7 and Station 8 and increases quantity at Station 2. Thus, each station for private EVs is optimally used for more efficient charging.

Fig. 18 illustrates a more even distribution of electric taxis using the optimized strategy when compared with traditional charging strategy.

5.3.3.2. Wait time for charging. The paper provides statistics of wait time for private EVs and electric taxis using different strategies.

Table 6 shows the statistical data for the time and the number of private EVs. Waiting EVs account for 2.74% of private EVs and the longest wait time is 45 min for the traditional strategy. With comprehensive optimization strategy, waiting EVs account for 1.46% of EVs in total and the longest waiting time is only 30 min.

Table 7 shows information about the wait time for taxi EVs. Data shows that the optimized strategy for taxis decreases the wait time and reduces the quantity of waiting vehicles.

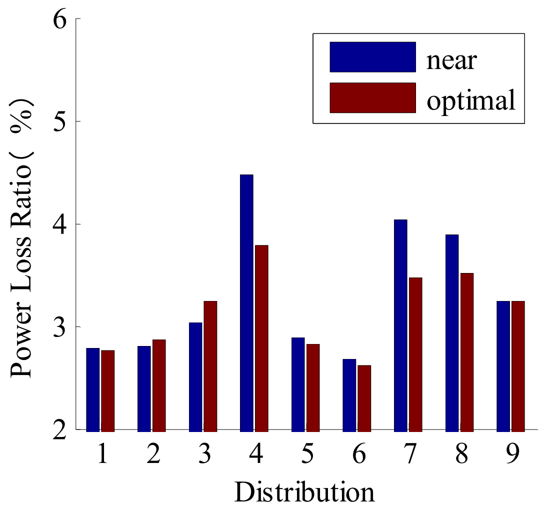

Fig. 15. Average loss rate for each power network.

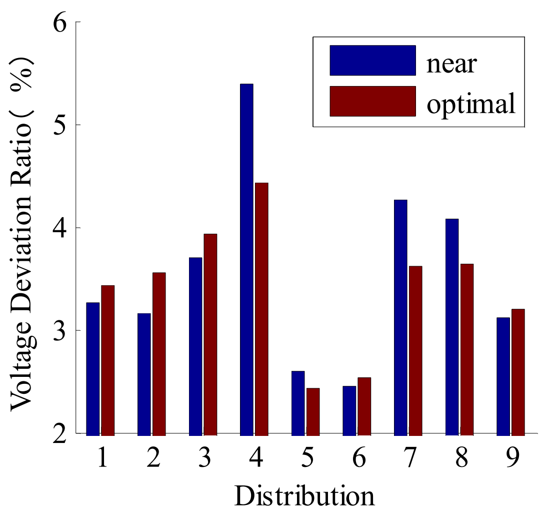

Fig. 16. Maximum voltage deviation rate for each station.

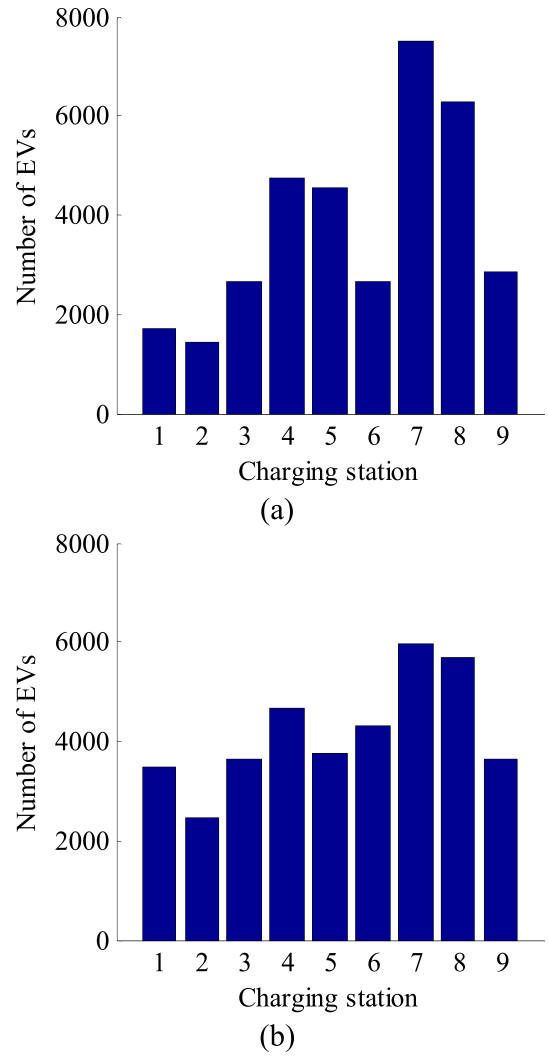

Fig. 17. Quantity of private EVs: (a) the traditional strategy (b) optimized strategy.

To recap, the proposed scheduling strategy can relieve local traffic jams, smooth network load curve, increase safety and economy of the power network, and decrease the number of charging electric vehicles in station. More importantly, the proposed method is universal and suitable for different cities or regions, although data differs depending on different cities or areas, such as travel characteristics, locations of charging stations, etc.

6. Conclusion

Based on the charging scheduling simulation platform, this paper offers a comprehensive optimal scheduling strategy for charging of different types of EVs in order to optimize EVs, transportation, power network, and stations.

The following conclusions are drawn:

1) Optimal charging scheduling strategy for private EVs and EV taxis builds up objective functions integrating road speed, charging loads and EV quantity at stations, comprehensively considering driving, loads and operation of power network while optimizing the overall system.
2) During rush hour, local traffic congestion attributed to high demand in charging by EVs is alleviated and traffic speed near stations is increased. The optimal strategy can improve the traffic capacity of road.
3) The charging load distribution of each station is more even. Furthermore, the larger power loss rate and voltage deviation rate diminish and fall within a safe range of values. Optimal charging strategy can smoothen charging load curves and enhance safety and economics of the power network operation.
4) The proposed strategy more evenly distributes the quantity of EVs amongst charging stations while reducing the longest waiting time and the quantity of waiting vehicles. Ultimately, comprehensive optimal scheduling strategy can increase the efficiency of charging infrastructure and improve convenience of charging users.
5) A universal simulation system is built up, and 24-h simulation test is performed on the charging scheduling within Beijing's three ring area. Comparative simulation is carried out to validate the benefit of this proposed method.

Declaration of competing interest

There is no conflict of interest form.

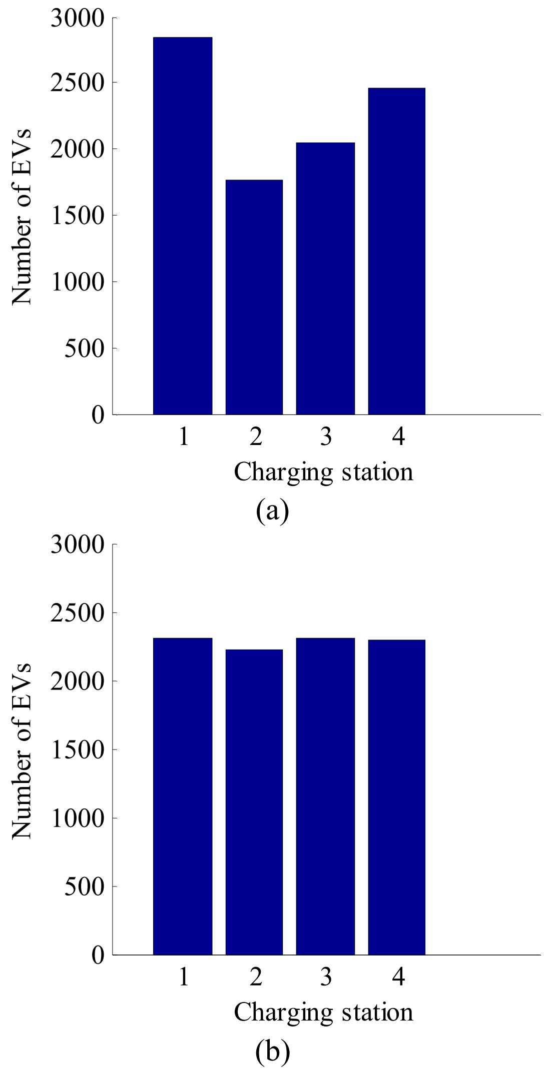

Fig. 18. Quantity of electric taxis at station: (a) the traditional strategy (b) optimized strategy.

Table 6
Waiting time for private EV.

Time (min)	Traditional strategy	Optimized strategy
0–10	935	1035
10–30	2179	670
30 and above	84	0
Total	3198	1705

Table 7
Waiting time for taxi EV.

Time (min)	Traditional strategy	Optimized strategy
0–30	2394	2581
30 and above	276	4
Total	2667	2585

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