Electric vehicle charging guidance based on weighted complex network

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**ABSTRACT**
The charging station malfunction may deny the charging service for the electric vehicles at the station. As a result, the vehicles need to select other stations. How to make an optimal selection is difficult for the owners. An optimal charging guidance strategy based on a weighted complex network is proposed for the owners to select the optimal station. All the charging stations are modelled as a complex network in which the stations and the roads among them are defined as nodes and edges, respectively. Furthermore, each edge is weighted by the state of charge (SOC) of the vehicle, the charging price, and the distance and traffic conditions between these two stations. The bigger edge weight indicates the smaller probability that the owner at one node of the edge select the other node of the edge for charging, and vice versa. Based on the weighted complex network model, the local load redistribution method is presented to guide the charging of vehicles at the malfunctioning station. Consequently, the optimal scheduling of the vehicles is realized under the guidance strategy proposed in this paper. Finally, some contrast experiments are carried out to illustrate the effectiveness and the superiority of the proposed method.

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1. Introduction
With the adjustment of national energy strategy, building a new energy dominated new-type power system is the key way to achieving the target of carbon peaks and carbon neutrality. Furthermore, the dissemination and application of electric vehicles is an important link to promote energy transformation and development (Mei et al., 2020; Li, liu et al., 2021). However, the current construction of charging stations does not match the charging demand of electric vehicles, which brings great pressure and challenges against the development of electric vehicles. Therefore, it is urgent to adopt an effective charging scheduling strategy to guide the charging behaviour of electric vehicle owners. It can better meet the charging demand and improve owners charging satisfaction.

Aiming at the problem of the charging scheduling of electric vehicles, some effective methods have been given. Literatures (Li et al., 2020; Li, lu et al., 2021; M. Wang, Lyu, et al., 2022; K. Wang, Wang, et al., 2022) proposed the real-time electricity price and V2G price incentive strategy to realize a win-win situation for both the power grid and electric vehicle users. Literatures (Al-Obaidi et al., 2021; Kim et al., 2022; Yin et al., 2021) proposed the electric vehicle scheduling strategy considering user preferences to improve the profit of charging operators and the satisfaction of electric vehicle users. Literatures (Hu et al., 2022; Liu, 2022; Zheng & Yao, 2021) studied the location and capacity optimization scheme of charging stations, and satisfied the charging demand of electric vehicles. Literature (Huang et al., 2017) proposed a destination-oriented charging guiding strategy, which can take both charging station capacity and owners’ travelling demand into consideration. Literature (Ren et al., 2019) proposed a charging navigation strategy by guiding the driving the behaviour of electric vehicle users based on the time-of-use electricity price of the power grid.

The above studies have paid attention to electricity price incentive, user participation, location and capacity of charging stations, charging guide and so on. However, the development of complex network theory provides a new idea for the research of electric vehicle. Literature (Huang et al., 2022) proposed an agent-based evolutionary game model to rethink the dynamics of charging station diffusion in a complex network to drive charging station diffusion. Literature (Wu et al., 2021) proposed a method for evaluating the charging and discharging scheduling potential of electric vehicles in case of the occasional operation of a power grid, and established an
evolutionary game model for the optimal response in a complex network to study the response rule of the users for the scheduling measures.

Due to natural disasters, equipment failures or human factors, there will be the charging station malfunction. Therefore, the charging station may deny the charging service for the electric vehicles at the station, which greatly reduces the owner’s charging satisfaction. The vehicles queued at a faulty charging station or the vehicles planned to charge at the station need to be guided to select an optimal alternative. The main contribution of this paper is to propose an optimal charging guidance strategy based on a weighted complex network for the owners to select the optimal station. Firstly, all the charging stations are modelled as a complex network in which the stations and the roads among them are defined as nodes and edges respectively. Secondly, each edge between some two stations are weighted by the SOC of the electric vehicle, the charging price, and the distance and traffic conditions between these two stations, so as to form a weighted complex network. Based on the weighted complex network model, the local load redistribution method is presented to guide the charging of electric vehicles at the malfunctioning station. Finally, some contrast experiments are carried out to illustrate the effectiveness and the superiority of the model and method.

The contents of this paper are as follows. Section 2 establishes the weighted complex network model of charging station. And then, section 3 presents the local load redistribution method based on the weighted complex network. Subsequently, section 4 demonstrates the feasibility of the model and charging guidance strategy through some contrast experiments. Finally, section 5 concludes the paper and gives some future work.

2. System modelling

The charging station malfunction may deny the charging service for the electric vehicles at the station. As a result, the affected electric vehicles need to select an adjacent charging station for charging. The distribution of charging stations in this paper is shown in Figure 1, where the blue solid line represents the road connection between charging stations.

Based on the distribution of charging stations, the charging stations are defined as nodes, the connections road between charging stations are defined as edges, and the probability of charging station being selected by the owner of electric vehicle is set as the weight of the connecting edge. Finally, we can obtain an undirected weighted graph based on the complex network methods (Chen et al., 2022; Huang et al., 2015; Kumar & Panda, 2022; Yuan et al., 2022). The undirected weighted graph is denoted by \( G = (V, E, W) \). The \( G \) consists of the node collection \( V \), the edge collection \( E \) and the weight collection \( W \), where \( V = \{v_1, v_2, \ldots, v_N\} \) (assuming that there are \( N \) charging stations), \( E = \{e^i\} \) and \( W = \{\omega^i\} \). The connections between the nodes is defined as an adjacency matrix \( A = (a^{ij}) \subset R^{N\times N} \). When there is a connection between node \( i \) and node \( j \) (i.e. \( e^i = (i, j) \subset E \)), \( a^{ij} = 1 \). Otherwise, \( a^{ij} = 0 \). The \( W = \{\omega^i\} \) denotes the weight of edge \( e^i \), where \( 0 \leq \omega^i \leq 1 \). As a result, based on the above analysis and modelling, the weighted complex network model of charging station model is proposed. The model is shown in Figure 2.

![Figure 1. The distribution of charging stations.](image1)

![Figure 2. The weighted complex network model of charging station model.](image2)
3. Optimal charging scheduling of electric vehicles

When the charging station fails, the affected electric vehicles need to select other stations. Therefore, an optimal charging guidance strategy based on a weighted complex network is proposed for the owners to select the optimal station. Then, based on the weighted complex network model, the local load redistribution method is presented to guide the charging of electric vehicles affected. Finally, the owner’s charging satisfaction is defined to verify the rationality of the guidance strategy.

3.1. Weighted complex network weight solution

When the charging station $i$ fails, the affected owners will consider selecting its adjacent charging station $j$ for charging service. However, the selection of owners is usually affected by the SOC of electric vehicles, the distance between charging stations, the price of charging station and the traffic conditions between charging stations. Considering the above factors, a reasonable weight expression is selected as follows:

$$
\omega_{ij}^{d} = ax_{ij} + by_{ij} + c\delta_{ij} \quad (1)
$$

In (1), the parameter $\omega_{ij}^{d}$ represents weight, that is, the probability of the $d$th vehicle served from the charging station $i$ to the charging station $j$ when the charging station $i$ fails. The bigger weight indicates the smaller probability that the affected vehicle owner select the charging station $j$; the parameter $x_{ij}$ represents the distance between charging station $i$ and adjacent charging station $j$, the larger $x_{ij}$ indicates the farther distance; the parameter $y_{ij}$ represents the traffic condition between charging station $i$ and adjacent charging station $j$, the larger $y_{ij}$ indicates the more traffic congestion; the parameter $\delta_{ij}$ represents the electricity price of the adjacent charging station $j$, the larger $\delta_{ij}$ indicates the higher electricity price. $a, b$ and $c$ represent their proportions respectively, satisfy the following constraint $0 < a, b, c < 1, a + b + c = 1$.

When the owner selects the target charging station, if the SOC of the affected electric vehicle is low, the owner will give priority to the nearest adjacent charging station (even if the adjacent charging station has higher electricity price or more congested traffic). In this case, the distance in the weight expression accounts for a higher proportion. Otherwise, the distance in the weight expression accounts for a lower proportion. Therefore, it can be obtained that the SOC of electric vehicle (2) is negatively correlated with the proportion $a$ of the distance between the charging station. Through the fitting of the charging history data of owners, the relationship between them can be obtained as an exponential relationship $a = \mu^{2}$, where the parameter $\mu$ is a constant and $0 < \mu < 1$. When the SOC of the electric vehicle is determined, the distance between charging stations is the main factor affecting the choice of the owner, and the price of charging station and the traffic condition between charging stations are secondary factors. This paper assumes that two secondary factors have the same degree of influence, that is, the parameter $b$ is equal to parameter $c$. The parameter $a$ can be determined according to the affected electric vehicle SOC, and the constraint $a + b + c = 1$ need be satisfied. Then we can obtain $b = c = 0.5(1 - a) = 0.5(1 - \mu^{2})$. In summary, the weight formula can be obtained as follows.

$$
\omega_{ij}^{d} = \mu^{2}x_{ij} + 0.5(1 - \mu^{2})y_{ij} + 0.5(1 - \mu^{2})\delta_{ij} \quad (2)
$$

In (2), the parameter $Z_{j}^{d}$ represents the SOC of the $d$th electric vehicle in charge station $i$.

The weight set in this paper is related to the SOC of electric vehicles, the distance between charging stations, the price of charging station and the traffic condition between charging stations. The distance between charging stations and the price of charging stations are variables that can be determined after charging stations being put into use. However, the traffic condition between charging stations involves many factors, such as road traffic volume, actual travel speed, etc.

According to the research on traffic congestion in literatures (Mehdi et al., 2022; Nagy & Simon, 2021; Wang, Zhou, et al., 2022; Ye & Yang, 2021), the traffic congestion index is roughly related to the factors such as the speed of road restriction, traffic density, actual travel speed and road traffic volume. In addition, road information and traffic flow information will also affect traffic congestion indicators to some extent. In this paper, the speed limit $V_{ka}$, the actual average speed $V_{kt}$, the number of lanes $n$, the width of each lane $l$, the average area of vehicles and their parking spacing $S$, the driving time of vehicles on the road $t$, and the number of vehicles entering the road within $t$ time $Q$ are comprehensively considered. Then the road congestion coefficient $\alpha$ is defined as follows (Wang, Zhou, et al., 2022).

$$
\alpha = Q \ast (t \ast V_{ka} \ast l \ast n \ast S^{-1})^{-1} \ast V_{kt} \quad (3)
$$

In (3), when the number of vehicles on the road is certain, the smaller $l$ and $n$ will generate the greater density of vehicles on the road, further reduce the vehicle speed and the number of vehicles entering the road within a certain time. As a result, the smaller the congestion coefficient, the more congested the road (Wang, Zhou, et al., 2022).

The calculation formula of traffic condition $y_{ij}$ between charging station $i$ and charging station $j$ is defined as
the number of electric vehicles served by charging station
In (6), the parameter $Q_{ij}$ represents the number of vehicles entering the road between charging station $i$ and charging station $j$; the parameter $V_{d}$ represents the speed of the vehicle on the road between charging station $i$ and charging station $j$; the parameter $n_{ij}$ represents the actual average speed of the vehicle on the road between charging station $i$ and charging station $j$. The number of electric vehicles served by the charging station $i$ is used as the attribute index of the charging station service ability (Liu et al., 2021; Lee & Hu, 2019).

Combined formulas (2) and (4), the weight $\omega_{ij}$ of the $d$th vehicle served from the charging station $i$ to the charging station $j$ when the charging station $i$ fails can be obtained, as shown in the following equation:

$$\omega_{ij} = \alpha_{ij}^{-1} = [Q_{ij} \ast (t \ast V_{d} \ast l_{ij} \ast n_{ij} \ast S^{-1})]^{-1} \ast V_{d}^{-1}$$

(4)

3.2. Charging guidance based on local load redistribution

In this paper, the upper limit of the number of electric vehicles served by the charging station is used as the attribute index of the charging station service ability (Liu et al., 2021; Xing et al., 2020). The upper limit of the number of electric vehicles served by charging station $i$ is positively correlated with the initial number of electric vehicles, presented as follows:

$$C_{i}^{\max} = (1 + \beta) C_{i}$$

(6)

In (6), the parameter $C_{i}^{\max}$ represents the upper limit of the number of electric vehicles served by charging station $i$; the parameter $C_{i}$ represents the initial number of electric vehicles served by charging station $i$; the parameter $\beta$ represents tolerance coefficient.

3.2.1. Local load redistribution without considering weight

When the charging station $i$ fails, its adjacent charging station node $j$ will share the number of additional electric vehicles from the charging station node $i$ according to a certain proportion of $p_{ij}$. The number of additional electric vehicles $\Delta C_{ij}$ is calculated as follows (Kaviani & Hedman, 2021; Lee & Hu, 2019):

$$\Delta C_{ij} = p_{ij} \ast \tilde{C}_{j}$$

(8)

In (7) and (8), the parameter $p_{ij}$ represents the proportion of the number of electric vehicles in charging station $j$ in the total number of electric vehicles in the neighbor charging stations of charging station $i$, the parameter $\Gamma_{i}$ represents the set of neighbor charging stations of charging station $i$, the parameter $C_{j}$ represents the number of electric vehicles initially served by the charging station node $j$, the parameter $\tilde{C}_{j}$ represents the number of electric vehicles to be allocated by the charging station node $i$.

The number of electric vehicles $\tilde{C}_{j}$ in charging station $j$ after local load redistribution without considering the weight is calculated as follows:

$$\tilde{C}_{j} = C_{j} + \Delta C_{ij}$$

(9)

3.2.2. Local load redistribution considering weight

When the charging station $i$ fails, calculate the weight of each adjacent charging station selected by the $d$th affected electric vehicle. Then, the $d$th electric vehicle is assigned to the adjacent charging station corresponding to the minimum weight, and the adjacent charging station corresponding to the minimum weight is denoted as $m_{d}$. It is expressed in mathematical language as follows:

$$\arg \min_{j \in \Gamma_{i}} \omega_{ij} = m_{d}(m_{d} \in \Gamma_{i}, d \in D_{i})$$

(10)

In (10), the parameter $D_{i}$ represents the set of affected vehicles in charging station node $i$, and $D_{i} = \{1, 2, \ldots, d, \ldots, \tilde{C}_{i}\}$. Taking Figure 3 as an example, Figure 3 describes the distribution diagram of the $d$th affected electric vehicle considering the weight.

Through Equation (10), the distribution results of all affected electric vehicles can be obtained, which is
denoted as \( \{m_1, m_2, \ldots, m_d, \ldots, m_c\} \). Finally, the number of electric vehicles allocated to each adjacent node is counted, as follows:

\[
\tilde{C}_i = \sum_{d=1}^{c} \delta(m_d = k) = \Delta C_{i,k}^w \tag{11}
\]

In (11), the parameter \( k \) represents the adjacent charging station of charging station node \( i \), and \( k \in \Gamma_i \); the parameter \( \Delta C_{i,k}^w \) represents the number of electric vehicles assigned to adjacent charging station node \( k \) considering the weight.

Combined formulas (10) and (11), we can get the expression as follows:

\[
\Delta C_{i,k}^w = \sum_{d=1}^{c} \delta \left( \arg \min_{j \in \Gamma_i} \omega^d_j = k \right) \tag{12}
\]

The number of electric vehicles \( \tilde{C}_i^w \) in charging station \( k \) after local load redistribution considering the weight is calculated as follows:

\[
\tilde{C}_i^w = C_k + \Delta C_{i,k}^w \tag{13}
\]

In (13), the parameter \( C_k \) represents the number of electric vehicles initially served by the charging station node \( k \).

### 3.3. The owner’s charging satisfaction

The charging station malfunction may deny the charging service for the electric vehicles at the station. Then an optimal charging guidance strategy based on a weighted complex network is proposed for the owners to select the optimal station. Finally, the rationality of the guidance strategy can be evaluated by calculating the charging satisfaction of the owner.

#### 3.3.1. Queuing waiting satisfaction

The operation index of charging station can be obtained by \( M/M/r/\infty/h \) queuing model (Han, 2007; Si et al., 2021):

The average number \( L_s \) of owners who are charging or waiting for charging in the queue:

\[
L_s = \sum_{f=1}^{h} fP_f \tag{14}
\]

The average number \( L_q \) of owners who are waiting for charging in a queue:

\[
L_q = \sum_{f=r+1}^{h} (f - r)P_f \tag{15}
\]

The waiting time \( W_q \) of the charging station:

\[
W_q = \frac{L_q}{\lambda_e} \tag{16}
\]

In (14)–(16), the parameter \( \lambda_e \) represents the effective arrival rate of the system and can be calculated as \( \lambda_e = \lambda(h - L_s) \), the parameter \( \lambda \) represents the electric vehicles’ arrival is independent and identically distributed, and is assumed to follow Poisson distribution with mean \( \lambda \); the parameter \( P_f(f = 0, 1, \ldots, h) \) represents the probability that \( f \) electric vehicles are charging at the station; the number of total service desks is defined as \( r \) that is actually the number of charging piles at the charging station; the parameter \( h \) defines the number of customer sources (i.e. the number of electric vehicles served by the station). When \( 0 \leq f \leq r \), the number of electric vehicles waiting for charging is not larger than the number of charging piles, and there is no queue line. When \( f > r \), the number of electric vehicles waiting for charging is larger than the number of charging piles, and there are \( (f - r) \) electric vehicles in the queue line.

The queuing waiting satisfaction is defined as \( Q_{wl} \) and inversely relates to the waiting time \( W_q \) and the number \( L_s \). The larger \( W_q \) and \( L_s \) will generate the less \( Q_{wl} \). Based on the definition in Literature, The queuing waiting satisfaction \( Q_{wl} \) is calculated as follows:

\[
Q_{wl} = \frac{1}{W_q \ast L_s} \tag{17}
\]

#### 3.3.2. Charging guidance satisfaction

This paper designs electric vehicle charging guidance strategy based on weighted complex network. Then, the weight expression is set up by considering the SOC of the affected electric vehicle, the distance between the charging stations, the price of the charging station and the traffic conditions between the charging stations. The smaller weight indicates the bigger probability that the affected vehicle owner selects the adjacent charging station, and the higher satisfaction of charging guidance. After the failure of charging station \( i \), the charging guidance satisfaction \( Q_{cohj}^d \) of the affected \( d \)th electric vehicle to the adjacent charging station \( j \) is defined as follows:

\[
Q_{cohj}^d = \frac{1}{\omega_{ij}^d} \tag{18}
\]

#### 3.3.3. The owner’s charging satisfaction

According to the different preference of owners for queuing waiting and charging guidance strategy, the owner’s charging satisfaction can be established. The charging satisfaction of the electric vehicle owner who is not affected after the failure of the charging station \( i \) is equal
to the queuing waiting satisfaction of the selected charging station. The calculation formula is shown in Equation (17). When the charging station \( i \) fails, the weight is considered when redistributing the affected electric vehicles. The charging satisfaction of the affected owners is not only related to the queuing waiting satisfaction after redistribution, but also related to the satisfaction of charging guidance. This paper defines the charging satisfaction of affected electric vehicle owners as follows:

\[
Q^d = \chi Q^d_{\text{wl},j} + \xi \tilde{Q}^d_{\text{ow},ij}
\]  

In (19), the parameter \( Q^d \) represents the owner’s charging satisfaction of the affected \( d \)th electric vehicle after the failure of charging station \( i \); the parameter \( Q^d_{\text{wl},j} \) represents the queuing waiting satisfaction of the affected \( d \)th electric vehicle after local load redistribution; the parameter \( \tilde{Q}^d_{\text{ow},ij} \) represents the satisfaction of the charging guidance of the affected \( d \)th electric vehicle redistributed to the charging station \( j \) after normalization; \( \chi \) and \( \xi \) represent the proportion of queuing satisfaction and charging guidance satisfaction respectively, satisfying \( 0 \leq \chi, \xi \leq 1, \chi + \xi = 1 \).

4. Example analysis

4.1. Experiment 1: electric vehicle charging guidance based on complex network

The charging station model based on complex network in the Experiment 1 contains 14 charging station nodes, between which the connection is shown in Figure 4. The number of charging piles and electric vehicles corresponding to each charging station in the Experiment 1 is shown in Table 1, and the distance between charging stations is shown in Table 2.

When the charging station node \( i(i \in \{1, 2, \cdots, 14\}) \) fails, the affected electric vehicle is allocated to adjacent node \( j(j \in \{1, 2, \cdots, 14\}, j \neq i) \) by local load redistribution without considering the weight. In this paper, the load tolerance coefficient \( \beta \) is set to 0.4. After local load redistribution, if \( C_j > C_{\text{max},j} \), the local load redistribution method is used again until the number of electric vehicles at all charging station nodes does not exceed its upper limit. The steps of the proposed electric vehicle charging guidance algorithm based on the complex network are as follows (Table 3).

Randomly select No. 4, No. 7, No. 8, No. 10, No. 13 charging station node as failure, and the charging guidance results of electric vehicles based on local load distribution are shown in Table 4. In Table 4, the 5 (7 vehicles) indicates that the 7 electric vehicles served by the No. 4 fault charging station are guided to the No. 5 charging station for charging.
Table 4. Charging guidance results for the affected electric vehicles.

| Fault charging station node | Charging guidance results for electric vehicles |
|-----------------------------|-----------------------------------------------|
| 4                           | 5 (7 electric vehicles), 3 (6 electric vehicles), 7 (6 electric vehicles), 2 (1 electric vehicles), 8 (1 electric vehicles) |
| 7                           | 4 (8 electric vehicles), 5 (1 electric vehicles), 8 (5 electric vehicles), 9 (1 electric vehicles) |
| 8                           | 7 (6 electric vehicles), 4 (2 electric vehicles), 9 (5 electric vehicles) |
| 10                          | 11 (7 electric vehicles), 6 (3 electric vehicles), 9 (5 electric vehicles), 8 (1 electric vehicles), 14 (2 electric vehicles) |
| 13                          | 12 (8 electric vehicles), 14 (5 electric vehicles) |

Table 5. Charging guidance results of the affected electric vehicles.

| Guide to the charging station node | Charging guide results |
|-----------------------------------|------------------------|
| 11                                | 7 electric vehicles (54%, 36%, 27%, 31%, 29%, 36%, 37%) |
| 6                                 | 3 electric vehicles (21%, 24%, 48%) |
| 9                                 | 5 electric vehicles (22%, 23%, 32%, 49%, 33%) |
| 8                                 | 1 electric vehicles (34%) |
| 14                                | 2 electric vehicles (20%, 36%) |

Although the charging guidance for the affected electric vehicles is completed, the SOC of the affected electric vehicles is not considered.

Generally, the charging behaviour of owners is flexible, so the SOC of electric vehicles to start charging is random. Therefore, in this paper, the SOC of electric vehicle is set as follows: 30% of owners choose to charge the SOC at 20%–30%, 40% of owners choose to charge the SOC at 30%–40%, 20% of owners choose to charge the SOC at 40%–50%, and 10% of owners choose to charge the SOC at 50%–60%.

After the failure of the charging station, the SOC of the electric vehicle is considered when charging based on the complex network. Then, No. 10 charging station node failure is taken as an example to do charging guidance analysis. There are 18 electric vehicles affected by No. 10 charging station, of which SOC is 22%, 23%, 36%, 54%, 27%, 34%, 31%, 29%, 32%, 48%, 21%, 24%, 36%, 49%, 33%, 20%, 37% and 36%, respectively. Then the local load redistribution method without considering the weight is used to guide the charging of the affected electric vehicles. The results are shown in Table 5.

In Table 5: the 7 electric vehicles (54%, 36%, 27%, 31%, 29%, 36%, 37%) indicate that when No. 10 charging station was faulty, the 7 electric vehicles with SOC of 54%, 36%, 27%, 31%, 29%, 36%, 37% were guided to No. 11 charging station. However, electric vehicles with lower SOC may be guided to farther charging stations (electric vehicle with a SOC of 20% is guided to the farther No. 14 charging station and electric vehicle with a SOC of 21% is guided to farther No. 6 charging station). Moreover, electric vehicles with higher SOC may be guided to closer charging stations (electric vehicle with a SOC of 54% is guided to the closer No. 11 charging station).

4.2. Experiment 2: electric vehicle charging guidance based on weighted complex network

In Experiment 1, the modelling of charging station nodes based on complex network only considered topological connections between charging stations. But, electric vehicles with lower SOC may be guided to farther charging stations. Obviously, this scheduling result does not meet the actual demand. To solve the above problems, in Experiment 2, the charging station model based on weighted complex network was established, as shown in Figure 5. Then, the weight in the complex network is set by comprehensively considering the affected EV SOC, the distance between charging stations, the electricity price of charging stations and the traffic condition between charging stations. The number of electric vehicles and charging piles configured by each charging station in Experiment 2 is shown in Table 1, and the SOC settings of electric vehicles served by each charging station are the same as Experiment 1.

In Figure 5, the edge weight represents the probability that the owner of one node on the edge selects another node on the edge to charge. For example, the parameter \( \omega_{12}^d \) represents the probability that the \( d \)th electric vehicle it serves will be assigned to the No.2 charging station when the No.1 charging station fails. The charging station price and the road section information between charging stations are shown in Tables 6–7, and the distance between charging stations are shown in Table 2.

In general, the average length of household vehicles is 3.8–4.3 m, and the average width is 1.6–1.8 m. Moreover, considering the distance between driving and stopping,
the average floor area per vehicle was 10 m², that is, the parameter $S$ in (3) is equal to 10 (Wang, Zhou, et al., 2022). In Experiment 2 take $\mu = 0.1$ and $\beta = 0.4$. After the normalization of $x_{ij}$, $y_{ij}$ and $\delta_j$, the weight corresponding to the selection of charging stations with different targets for electric vehicles can be obtained according to formula (5). The bigger weight indicates the smaller probability that the vehicle selects the charging stations. The steps of the proposed electric vehicle charging guidance algorithm based on the weighted complex network are as follows (Table 8).

In Experiment 2, No. 10 charging station node failure is taken as an example for the charging guidance analysis. The local load redistribution method based on weighted complex network is used to guide the charging of affected electric vehicles, and the results are shown in Table 9.

In Table 9, when the No. 10 charging station fails, the electric vehicle with lower SOC will be guided to the nearest No. 11 charging station. Furthermore, the electric vehicle with higher SOC will be guided to the far-distance but low price and smooth traffic No. 9. Therefore, the local load redistribution based on weighted complex network is more realistic for the charging guidance of the affected electric vehicle.

### Table 6. Electricity price of charging station.

| Charging station | Electricity price $\delta$ (Yuan/kW·h) |
|------------------|----------------------------------------|
| 1                | 1.05                                   |
| 2                | 1.22                                   |
| 3                | 1.35                                   |
| 4                | 1.60                                   |
| 5                | 1.28                                   |
| 6                | 0.90                                   |
| 7                | 0.90                                   |

### Table 7. Road section information between charging stations.

| Road connection between charging stations | $n$ | $l$ | $V_{ud}$ (km/h) | $V_{ud}$ (km/h) | $t$ (min) | $Q$ |
|-----------------------------------------|-----|-----|-----------------|-----------------|----------|-----|
| 1, 2                                    | 2   | 3.0 | 60              | 9               | 3        | 135 |
| 2, 3                                    | 2   | 3.3 | 60              | 9               | 3        | 175 |
| 3, 4                                    | 4   | 3.3 | 60              | 9               | 3        | 183 |
| 4, 7                                    | 3   | 3.2 | 60              | 13              | 3        | 183 |
| 7, 8                                    | 2   | 3.3 | 50              | 6               | 3        | 59  |
| 8, 9                                    | 2   | 3.3 | 60              | 6               | 3        | 86  |
| 9, 10                                   | 3   | 3.2 | 60              | 12              | 3        | 165 |
| 9, 14                                   | 4   | 3.3 | 30              | 10              | 3        | 195 |
| 14, 13                                  | 4   | 3.2 | 50              | 8               | 3        | 156 |
| 10, 11                                  | 2   | 3.3 | 60              | 5               | 3        | 71  |
| 11, 6                                   | 4   | 3.3 | 60              | 9               | 3        | 175 |
| 6, 12                                   | 2   | 3.0 | 30              | 7               | 3        | 106 |
| 12, 13                                  | 2   | 3.3 | 60              | 6               | 3        | 86  |
| 5, 6                                    | 4   | 3.3 | 30              | 10              | 3        | 195 |
| 5, 1                                    | 3   | 3.2 | 60              | 8               | 3        | 69  |
| 4, 5                                    | 2   | 3.3 | 60              | 6               | 3        | 86  |

### Table 8. Electric vehicle charging guidance algorithm based on the weighted complex network.

**Input:** The number of electric vehicles and charging piles configured by each charging station.

**Output:** Charging guidance results for the affected electric vehicles.

1. The charging station node $(i \in \{1, 2, \ldots, 14\})$ is randomly selected for failure.
2. Calculate the weight $\omega^d_{ij}$ of the affected electric vehicle allocated to the neighbour charging station $j$, where $j \in \Gamma_i$.
3. Then select the min $\omega^d_{ij}$ corresponding to charging station, the affected electric vehicle is assigned to the charging station.
4. Compare $\tilde{C}_j$ with $C_{\text{max}}^j$, if $\tilde{C}_j > C_{\text{max}}^j$, jump to step 5; else jump to step 6.
5. The local load redistribution method considering weight is introduced again, and the number of electric vehicles exceeding the upper limit is selected from the electric vehicle initially served by charging station $j$ for distribution.
6. Output the charging guidance result of the affected electric vehicles.

### Table 9. Charging guidance results of the affected electric vehicles.

| Guide to the charging station node | Charging guide results |
|-----------------------------------|------------------------|
| 9                                 | 36%, 54%, 48%, 36%, 49%, 37%, 36% |
| 11                                | 22%, 23%, 27%, 34%, 31%, 29%, 32%, 21%, 24%, 33%, 20% |

### 4.3. Experiment 3: Calculation of the owners’ charging satisfaction under different guidance strategies

In Experiment 1, the weight was not considered when the affected electric vehicles were redistributed. Therefore, the owner’s charging satisfaction is equal to the queuing waiting satisfaction of the selected charging station after redistribution. In Experiment 2, the weight is considered when the affected electric vehicle is redistributed. The owner’s charging satisfaction is the weighted average of queuing waiting satisfaction and charging guidance satisfaction. This paper takes $\chi = 0.8$, $\xi = 0.2$. 

| Guide to the charging station node | Charging guide results |
|-----------------------------------|------------------------|
| 3                                 | 36%, 54%, 48%, 36%, 49%, 37%, 36% |
| 11                                | 22%, 23%, 27%, 34%, 31%, 29%, 32%, 21%, 24%, 33%, 20% |
Moreover, some comparative experiments are carried out to show the superiority of the local load redistribution based on weighted complex network over the local load redistribution method. In our future research, we will consider the impact of changes in the network topology on the charging guidance strategy of electric vehicles after the failure of the charging station. In addition, we will also consider the subjective wishes of owners to further optimize and improve the charging guidance strategy to meet the charging demand and improve their charging satisfaction.

Table 10. The owners’ charging satisfaction under different guidance strategies.

| The affected electric vehicles | The Owners’ Charging Satisfaction (Electric Vehicle Charging Guidance Based on Complex Network) | The Owners’ Charging Satisfaction (Electric Vehicle Charging Guidance Based on Weighted Complex Network) |
|-------------------------------|-------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| 1(36%)                        | 0.095                                                                                            | 0.276                                                                                            |
| 2(54%)                        | 0.095                                                                                            | 0.076                                                                                            |
| 3(48%)                        | 0.211                                                                                            | 0.228                                                                                            |
| 4(49%)                        | 0.107                                                                                            | 0.131                                                                                            |
| 5(37%)                        | 0.095                                                                                            | 0.262                                                                                            |
| 6(36%)                        | 0.295                                                                                            | 0.436                                                                                            |
| 7(22%)                        | 0.107                                                                                            | 0.128                                                                                            |
| 8(23%)                        | 0.107                                                                                            | 0.143                                                                                            |
| 9(27%)                        | 0.095                                                                                            | 0.187                                                                                            |
| 10(34%)                       | 0.313                                                                                            | 0.45                                                                                            |
| 11(31%)                       | 0.095                                                                                            | 0.238                                                                                            |
| 12(29%)                       | 0.095                                                                                            | 0.214                                                                                            |
| 13(32%)                       | 0.107                                                                                            | 0.261                                                                                            |
| 14(21%)                       | 0.211                                                                                            | 0.198                                                                                            |
| 15(24%)                       | 0.211                                                                                            | 0.24                                                                                            |
| 16(33%)                       | 0.107                                                                                            | 0.272                                                                                            |
| 17(20%)                       | 0.295                                                                                            | 0.236                                                                                            |
| 18(36%)                       | 0.095                                                                                            | 0.276                                                                                            |

5. Conclusion

In this paper, an optimal charging guidance strategy based on a weighted complex network is proposed for the owners to select the optimal station. Firstly, the stations and the roads among them are defined as nodes and edges respectively, and the weighted complex network model of charging station is established. Then, the weight of the edge in the complex network is set by considering the factors such as the SOC of the affected electric vehicle, the distance between the charging stations, the electricity price of the charging station and the traffic condition between the charging stations, thus forming the weighted complex network model of the charging station. Next, based on the weighted complex network model, the local load redistribution method is presented to guide the affected electric vehicles. Finally, the model and charging guidance strategy are demonstrated to be effective by the simulation experiment.

Disclosure statement

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