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Modeling and Simulating of Private EVs Charging Load

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Abstract: As an important part of the smart grid, Electric Vehicles (EVs) could be a good measure against energy shortages and environmental pollutions. In this paper, based on the relevant EVs development policy, the private EVs charging load is investigated. Based on statistical data, the Monte Carlo method is applied to determine the one-trip driven distance for the private EV. And by analyzing the EVs driving habit and the charging characteristics of EVs battery, we derive the initial state-of-charge (SOC) of charging, charging power and initial charging time. As a result, a more accurate mathematical model of computing the charging load used by private EVs is proposed. Furthermore, the EVs charging loads in 2015 and 2020 are computed and compared in plug-in charging and wireless charging mode. The results of simulation show that the daily load peak of private EVs charging caused by wireless charging mode is significantly lower than that of plug-in charging mode. And the charging load of large-scale EVs would have significant impacts on the planning and operation of power grid. It is very important to predict and analyze the EVs charging load for the construction and scheduling of the smart grid in the future.

Keywords: Wireless charging, charging load, prediction, private EVs.

1. INTRODUCTION

The preceding scarcity of crude oil, serious environmental pollutions, growing carbon dioxide emissions and other factors initiated a "green" economy, resulting partly in the strive for more efficient individual transportation. Compared with Internal Combustion Engine Vehicles (ICEVs) which burn fossil fuels, Electric Vehicles (EVs) show the potential for solving the energy crisis and reducing the emissions of carbon dioxide. More and more governments, car manufacturers and energy companies have paid attentions on EVs and are getting active in EVs' development and production. July 9, 2012, China's State Council officially promulgated the "energy-saving and new energy automotive industry development plan (2012-2020)", and clearly pointed out that pure electric drive would be the main strategic orientation of the auto industry restructuring plan and the development of the automotive industry would focus on promoting the industrialization of Pure Electric Vehicles (PEVs) and Plug-In Hybrid Electric Vehicles (PHEVs) with the cumulative production and sales reaching 500,000 by 2015, and up to 5 million by 2020 [1].

Once a large-scale EVs access to the grid, they would lead to extra and undesirable electrical consumption peaks. Many scholars have studied the influence of EVs on the distribution grid over the past decade. Clement-Nyns K *et al.* introduced the stochastic programming technique to predict the load profiles and applied the quadratic programming to deal with the coordinated charging of PHEVs with one setting initial SOC and during a fixed period [2]. Shao S. *et al.* considered the varied EVs charging scenarios, but the initial charging time in every scenario was fixed [3]. Taylor J. *et al.* provided details of analytical framework to evaluate the impact of PHEV loading on the distribution system as part of a large, multi-utility collaborative study [4]. Luo Z. W. *et al.* investigated the charging modes and charging time of varied EVs [5]. Qian K. *et al.* calculated the EVs charging loads considering the price, EV charging scenario and permeability [6]. Now, the vast majority of researches are on the PHEVs or PEVs with wired charging model, rarely combined with the mileage of EVs in the acquisition of initial charging state and ignored the changing charging power during the charging process.

Recently, based on the wireless power transmission technology, wireless charging mode for EVs has been the hotspot pursued by major research institutions and vehicle manufacturers [7-9], which would play a better role in the interaction between the grid EVs to realize load shifting and absorb the new energy resources. The wireless charging mode would become the development tendency of EVs charging [10-12]. Furthermore, this charging model could disperse continuous charging time and reduce charging aggregation, so that there is difference in the charging load profiles.

This paper aims at predicting the private EVs charging load profile. First, the characteristics of two different EVs charging models are simply analyzed. Then, a more accurate

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mathematical model is proposed to compute the private EVs charging load by applying Monte Carlo method to obtain the single trip mileage, initial SOC, initial charging time and charging power according to the characteristics of battery and the driving habits. Finally, based on the relevant EVs development policy of China, the private EVs scales until 2015 and 2020 have been predicted and the load profiles are simulated respectively.

2. EVS CHARGING LOAD MODELING

There are many factors to influence the EVs charging load profile, such as EVs scale, charging model, initial SOC of charging, initial charging time, changing power and battery capacity.

2.1. Charging Model

The vehicle charging mode and battery swap mode are the main energy supply models for EVs. Vehicle charging mode means that EVs charge directly to complete the energy supply while stopping, and there is great randomness in charging time and place. Battery swap model is an indirect energy supply for EVs by replacing the un-fully charged battery by fully charged battery in the swap station with the characteristics of charging concentrating and easy to control battery charging process. In this paper, the modeling and prediction of private EVs charging load is just based on the vehicle charging mode.

Vehicle charging mode mainly includes two models: plug-in charging and wireless charging. Plug-in charging mode needs to build a large number of dedicated charging points or charging stations, while wireless charging mode could make full and effective use of land resources without the extra land and space by directly laying the power transmitting coils under the existing parking spaces or roads. Therefore, compared to the plug-in charging mode, the EVs wireless charging mode would disperse the charging time and reduce the charging aggregation. This model has more great interaction ability with the grid and plays an important role in load shifting.

Considering the development tendency of EVs charging model and the maturity of wireless charging technology, this paper predicts the EVs charging load profile based on a certain proportion of the two charging models. Then the study on the impact of large scale EVs on the grid would become more comprehensive and the further researches on EVs coordinating charging schedule would be carried out.

2.2. Battery Characteristics

A. Battery SOC

Many researches on battery characteristics have been comprehensively carried out [13, 14]. Corresponding to one charging current i_d, the battery status could be described by a battery SOC [15],

$$S(t_2) = S(t_1) + (\int_{t_1 \to t_2} i_d \, dt) / C_a(i_d) \tag{1}$$

Where, $S(t_1)$ and $S(t_2)$ represent the battery SOC at time t_1 and t_2 respectively; $C_a(i_d)$ stands for the battery effective capacity in Ah.

According to the Peukert Equation [16], $C_a(i_d)$ could be derived by the formula (2).

$$C_a(i_d) = i_d * C_p / (i_d)^k \tag{2}$$

Where, C_p is the Peukert capacity of battery in Ah; k is the Peukert exponent within the range of 1.1 to 1.3. For one specific battery, these two parameters are constant and C_p could be derived as

$$C_p = T * (C_N / T)^k \tag{3}$$

Where, C_N is the battery nominal capacity in Ah; T is the battery rated discharge time in h; C_N/T stands for the battery rated discharge current in A.

According to the formulas (1) - (3), a new SOC of battery could be obtained while charging after a period of time.

B. Battery Charging Voltage

Another obvious characteristic of EVs battery is that the charging voltage would be changed dynamically with the charging process. Taking into account the security issues, the lead-acid battery 240100 is mainly used to study in our laboratory, where 240100 indicates that the battery has the rated voltage of 240V and rated capacity of 100Ah. Fig. (**1**) is the relation curve of charging voltage and battery capacity.

In Fig. (**1**), the battery charging voltage is gradually increased with the increase of battery capacity. When the battery capacity is less than 10% and greater than 90%, the magnitude of charging voltage would increase larger than battery capacity, and increase gently in the remaining range of battery capacity.

2.3. Initial SOC of Charging

In a charging period, the power demand for EV charging is varied with time. It is necessary to obtain initial SOC of charging to determine the load generated by EV charging. The initial SOC of charging is a random function on the driving mileage since the last charging. Statistics data show that the vehicle one driving mileage is closed to logarithmic normal distribution and its probability density function is as follows [6]:

$$g(d;\mu,\sigma) = \frac{1}{d\sqrt{2\pi\sigma^2}} \exp[-\frac{(\ln d - \mu)^2}{2\sigma^2}], d > 0 \tag{4}$$

Where, d is the vehicle one driving mileage in Km; μ and σ denote the mean and standard deviation of the probability density function. For private vehicles, μ = 20.5 km and σ = 4.88 km. Fig. (**2**) shows the probability density distribution of the private vehicle one driving mileage.

Assuming that the SOC of battery decreases linearly with the mileage, we could estimate the initial SOC of charging by vehicle's mileage as follows:

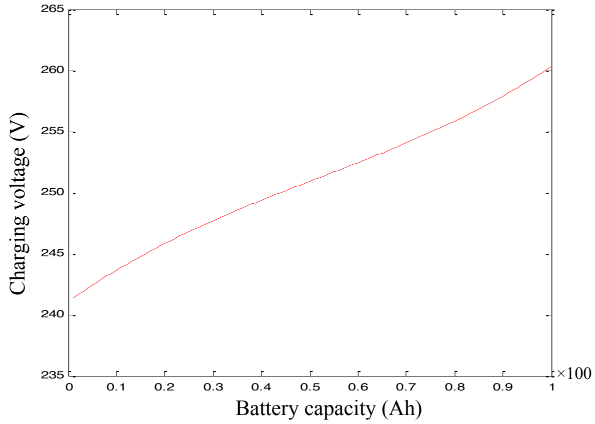

Fig. (1). Curve of the charging voltage and battery capacity.

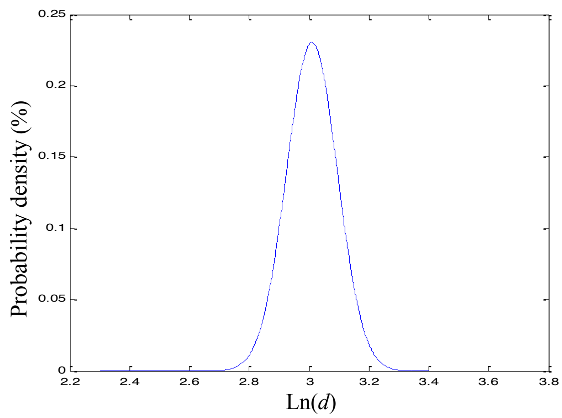

Fig. (2). Probability density distribution of the private vehicle one driving mileage.

$$\mathrm{SOC_i} = (\mathrm{SOC_0} - \alpha d / d_{\mathrm{full}}) \times 100\% \tag{5}$$

Where, SOC_i and SOC_0 represent the initial SOC of charging and the SOC after the latest charging respectively. In general, SOC_0 = 1. While in wireless charging mode, SOC_0 more often is not equal to 1 for dispersed charging time and charging locations. α is the EV travel times since the latest charging. d_{full} stands for the maximum mileage of the fully charged EV in km. Then the probability density distribution of SOC after one travel could be derived as follows:

$$p(\mathrm{SOC_i}) = \frac{1}{(\mathrm{SOC_0} - \mathrm{SOC_i}) d_{\mathrm{full}} \sqrt{2\pi\sigma^2}} \exp[-\frac{(\ln(\mathrm{SOC_0} - \mathrm{SOC_i}) + \ln d_{\mathrm{full}} - \mu)^2}{2\sigma^2}], 1 > \mathrm{SOC_i} > 0 \tag{6}$$

Compared to a typical d_{full} of 130 km, the one driving mileage of private EV is much shorter. So it is unnecessary for private EVs to charge after one travel and the means of SOC after one and two travel are closed to 84.2% and 68.5% respectively.

2.4. Initial Charging Time

Clearly, it is not possible that all of EVs begin to charge at the same time. The initial charging time of each individual vehicle is a random variable, which mainly depends on the electricity price and EV usage patterns. Assuming that the charging occurs as soon as EV stops at the destination, the initial charging time could be estimated by adding the departure time to the travel time.

Private vehicles are mainly used to work and participate in entertainment at weekend. The departure times of driving to work and back home after work are all comparatively concentrated. Table **1** describes in detail the departure time of private vehicle and the corresponding percentage in one day based on the statistics data [17, 18].

In Table **1**, there are two departure peaks at 6: 30-9: 30 and 16: 00-19: 00. During the two durations the road would be blocked and the average speed of vehicle is relatively low and set to 40 kph. In other times, the private vehicles depart dispersedly and would have a high average speed of 60 kph. Therefore, the initial charging time could be calculated by

Table 1. Departure time and corresponding vehicle percentage of private vehicle.

Departure Time	Percentage	Departure Time	Percentage	Departure Time	Percentage	Departure Time	Percentage
0:00-5:00	0.43%	8:31-9:00	4.92%	12:00-14:30	3.99%	18:01-18:30	4.63%
5:01-5:30	0.54%	9:01-9:30	1.55%	14:31-15:00	1.11%	18:31-19:00	4.43%
5:31-6:00	1.58%	9:31-10:00	1.39%	15:01-15:30	1.06%	19:01-19:30	1.18%
6:01-6:30	8.13%	10:01-10:30	0.48%	15:31-16:00	3.39%	19:31-20:00	2.94%
6:31-7:00	25.04%	10:31-11:00	0.66%	16:01-16:30	5.31%	20:01-20:31	1.19%
7:01-7:30	26.24%	11:01-11:30	0.83%	16:31-17:00	31.36%	20:31-21:00	0.26%
7:31-8:00	19.64%	11:31-12:00	0.36%	17:01-17:30	19.58%	21:01-24:00	4.88%
8:01-8:30	8.21%			17:31-18:00	14.06%		

Table 2. Percentages of various EVs.

Vehicle Type	Proportion	Vehicle Type	Proportion
Bus	65.52%	Office vehicle	4.67%
Taxi	15.52%	Vehicle rental	1.11%
Private vehicle	11.24%	Public domain vehicle	1.95%

random drawing driving mileage based on formula (4). Furthermore, for one private vehicle, there is an interval more than 8 hours between commuting to charge fully in workday. In view of this, the limit of charging duration is ignored when accumulating the private vehicle charging load, and it is namely that all vehicles would be charged fully from initial SOC of charging.

2.5. Charging Power

For the lead-acid battery with 100C rated capacity, the battery would be charged at 20A current and its charging duration from empty to full is closed to 5h. In Fig. (**1**), the charging voltage of the battery is varied with its capacity. As a result, the charging power would be changed. For batter predicting the load profile generated by EVS charging, the charging duration should be divided into k periods. For instance, if the period is set to half an hour, k would be 10, and 20 for the period of 15 minutes. At the beginning of each period, the battery capacity could be derived as follows:

$$\begin{cases} S(t_{1-}) = SOC_{\mathrm{i}} \\ S(t_{\mathrm{k}+}) = S(t_{\mathrm{k}-}) + \left(\int\limits_{t_{\mathrm{k}-} \to t_{\mathrm{k}+}} i_{\mathrm{d}}\, dt \right) / C_{\mathrm{a}}(i_{\mathrm{d}}), \mathrm{k} \geq 2 \\ S(t_{(\mathrm{j}+1)-}) = S(t_{\mathrm{j}+}), \mathrm{j} \geq 1 \end{cases} \tag{7}$$

Where, t_{k-} and t_{k+} denote the beginning and the end of the k^{th} period respectively. $S(t)$ and $V(t)$ stand for the SOC and charging voltage at t time. It is obvious that $V(t_{k+}) > V(t_{k-})$ in Fig. (**1**). For more accurately predicting the charging load, the charging voltage during k^{th} the period could be calculated as follows:

$$V(t_{\mathrm{k}}) = \frac{V(t_{\mathrm{k}-}) + V(t_{\mathrm{k}+})}{2} \tag{8}$$

Then, the charging power generated by all EVs in the k^{th} period could be expressed as:

$$P_{\mathrm{k}} = \sum_{j=1}^{n} (V_{\mathrm{j}}(t_{\mathrm{k}}) * i_{\mathrm{k,j}} / \eta) \tag{9}$$

Where, n represents the number of EVs. V_j (t_k) and $i_{d,j}$ represent the charging voltage and charging current of the j^{th} EV in the k^{th} period respectively. η represents the charging efficiency with 85% for wireless charging mode and 95% for plug-in charging mode.

3. SCALE ESTIMATION OF PRIVATE EVS

By the above analysis, we could obtain the daily load profile of private vehicle charging. And as the large scale EVs access to the grid, the load caused by EVs charging would have a serious impact on to the grid. In "Chinese Automotive Industry Development Report (2012)," it has been pointed out that by the end of November 2011, the total number of EVs participated in the demonstration running is about 11.5 thousand in 25 cities of China, which are mainly bus, taxi, private vehicle, office vehicle. The proportions of various EVs are as shown in Table **2** [19].

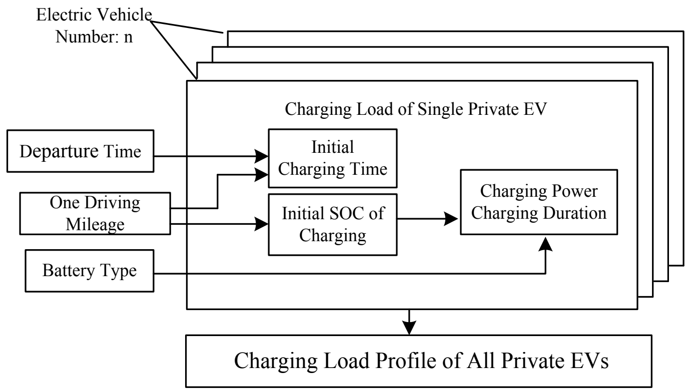

Fig. (3). Diagram of EVs charging load calculation.

As a good measure against energy shortages and environmental pollutions, the development of EVs has gained strong support of the government. Since last decade, the proportion of private vehicle has gradually increased year by year from 42.8% in 2001 to 76.12% in 2010. There is reason to believe that with the popularization of EVs, the proportion of private EVs would increase gradually to 30% in 2015 and 40% in 2020. According to data mentioned in the "energy-saving and new energy automotive industry development plan (2012-2020)", the number of private EVs is around 0.15 and 2 million in 2015 and 2020 respectively.

4. PREDICTION OF PRIVATE EVS CHARGING LOAD PROFILE

For calculating the charging load profile of private EVs, we used Monte Carlo method to draw one driving mileage and derive the initial charging time, the initial SOC of charging, the charging power based on the relevant statistical data and the charging characteristics of battery. Fig. (**3**) shows the structure diagram of calculating the charging load of private EVs.

In wireless charging mode, EVs are more conducive to participate in the interaction with the grid, in which way the power could feedback to the grid if necessary, and play an important role in load shifting. Therefore, in Fig. (**3**), the private EVs should be recharged after one driving to ensure that the batteries of EVs have a relatively high SOC as far as possible. Of course, from the perspective of the impact on the grid, recharging after one driving is one of the most undesirable charging scenarios.

Setting the number N of Monte Carlo simulation to 2000 and the variance D less than 5e-4, the flowchart of the private EVs load calculation is as shown in Fig. (**4**).

With the increase of EVs, a new load growth caused by EVs charging would be more and more significant to the grid. There would be two load peaks occurred in the morning and evening, when they are the two travel peaks of going to work and coming back from work in a day.

In wireless charging mode, the charging duration of private EV would be dispersed, and the ratio of charging occurring on the duty and off duty tends to be 0.5 to 0.5. As a result, the difference between the two peak loads would be small. For the plug-in charging mode, the percentage of charging in the resident parking lot after work would reach to 70% [5].

Setting the charging period to 15 minutes, the charging load profiles of private EVs based on wireless charging and plug-in charging in 2015 are as shown in Fig. (**5**).

In Fig. (**5**), due to disperse EV charging location and charging time, the private charging peak with wireless charg-

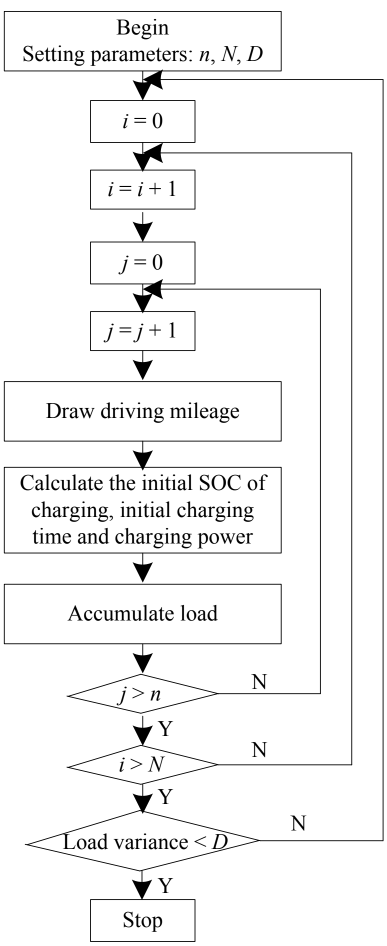

Fig. (4). Flowchart of private EVs charging load calculation.

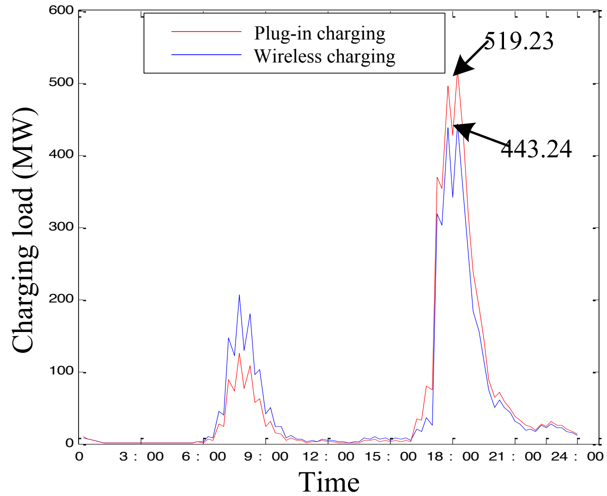

Fig. (5). Charging load profiles of private EVs in 2015.

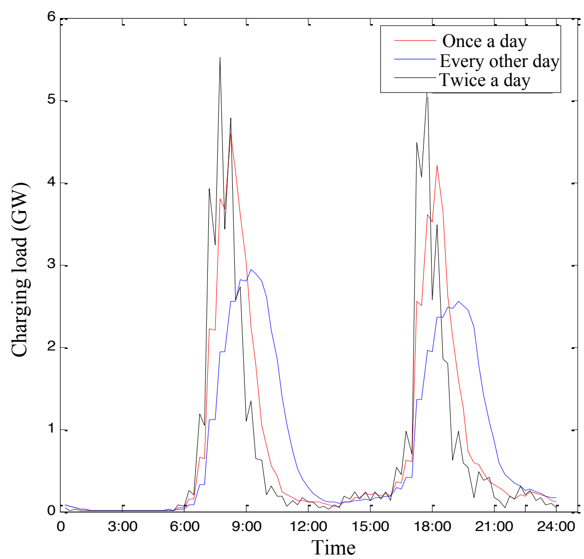

Fig. (6). Charging load profiles of private EVs in 2015 under various charging scenarios.

Table 3. Charging load peak load and average daily charging power.

Charging Scenario	Peak Load (GW)	Daily Average Charging Power (GW·h)
Twice a day	5.52	17.2
Once a day	4.58	18.58
Every other day	2.94	19.0

ing mode is 443.24 MW, decreased by 14.6% than that of 519.23MW with plug-in charging mode. Then the following simulations are carried out for wireless charging mode.

If EV charging occurs after one driving, EV would be charged twice a day and the initial SOC of charging would be a high mean of 84.2%. Then we consider charging EV after two or four ravels, and it implies that the EV charging would be once a day or every other day. Meanwhile, it is easy to calculate that the initial SOC means of the other two charging scenarios are 68.5% and 36.8%. In this case, the charging load profiles of private EV in 2020 could be calculated in various charging scenarios which are shown in Fig. (**6**).

In Fig. (**6**), in the scenario of every other day, the charging load peak is minimal and the charging duration is the longest due to the lowest initial SOC mean. Table **3** shows the peak loads and daily average charging powers of three charging scenarios.

In the charging scenario of twice a day, the peak load is maximal and the SOC of EV battery keeps constant at a high level (approximately close to 100%), which is an advantage to feedback more power to the grid by V2G system. In the other two charging scenarios, the peak load could reduce, however the SOC of EVs battery would be lower, which implies that the power feedback to the grid also becomes less. Therefore, while designing the V2G system, it is necessary to consider the peak load generated by EVs charging and the capacity of EV feedback to the grid.

CONCLUSION

Due to many uncertain factors, it is difficult to set up a precise mathematical model of calculating the EVs charging load. By analyzing the characteristics of the wireless charging mode, we apply Monte Carlo method to draw the one driving mileage of private EV, obtain the initial SOC of charging and charging power based on the characteristics of the EVs battery, estimate the initial charging time by adding the departure time to the travel time, and establish a more precise model to calculate the private EVs charging load. According to China's electric car development strategy and planning and relevant statistics, the simulation researches of predicting the load profiles of private EVs charging in 2015 and 2020 have been carried out. There is obvious difference between peak and valley load of the private EVs charging load profile, and the load peaks occur at 7: 00-8: 00 and 17: 00-19: 00, which is basically consistent with the whole network load peak periods. Due to dispersing of the EVs charging locations and charging time, the peak load in the wireless charging mode is 443.24 MW and decreases by 14.6% than that of 519.23 MW in the plug-in charging mode. Furthermore, we calculate the charging load profiles of the private EVs in three charging scenarios in 2020, and the results have a certain reference value for the design of V2G system in the future.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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