Modeling and Impact Analysis of large scale V2G Electric Vehicles on the Power Grid

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***Abstract*—With the rapid development of smart grid, the large scale vehicle-to-grid (V2G) electric vehicles (EVs) will been widely applied. However, the interaction between EVs and the power grid will bring many challenges. In order to lighten the adverse influence on the grid operation, the regional EV load should be estimated in advance. By thoroughly considering the impact factors of regional EV load on the gird, this paper presents a methodology to determine the regional EV load. Monte Carol simulation algorithm is adopted to draw the random numbers of impact factors and to achieve the simulation of EV load curve. Three kinds of EV load models are built and simulated including uncontrolled charging model, controlled charging model and controlled charging/discharging model. The impact of three different EV load models on the grid load curve and on the load rate and peak-valley difference of the grid is given in this paper. And the impact of different scale of EVs on the grid is also discussed. The EVs in Qingdao Economic and Technological Development Zone (QETDZ) in Qingdao city, Shandong Province, China are taken as an example to analyze the impact on the grid of different regional EV load models. The simulation results show that the three EV load models built in this paper are helpful to study the impact on the power grid and have a potential value in practical applications.**

Keywords-electric vehicle (EV); Monte Carol simulation; V2G; peak-valley difference

I. INTRODUCTION

VEHICLE-to-grid (V2G) mode is a kind of bidirectional energy exchange model in which plug-in electric vehicles (EVs) communicate with the power grid to sell demand response services by either delivering electricity into the grid or by throttling their charging rate[1][2]. The large scale application of V2G EV will bring a potential influence on the power grid [3-13]. It will increase the grid load, on the other hand it can also provide ancillary service by transferring electricity to the power grid as a smart energy storage unit.

Currently, several studies have been conducted on the modeling of EV load and its impact on the grid. Reference [4] develops mathematical model of Plug-in Hybrid Electric Vehicles (PHEVs) combined with distribution system components model, and the developed model is used to study the impact of uncoordinated and coordinated charging of PHEVs in distribution system. Oak Ridge National Laboratory (ORNL) is developing simulation models and energy management scenarios using the actual solar production and residential energy usage data, and a PHEV [5]. Reference [6] studies the impact of EVs on the grid in different scenarios with different seasons. Methodology for modeling and analyzing of the load demand in a distribution system due to EV battery charging are presented in reference [7][8]. Reference [9] proposes a coordinate charging strategy with the goal to minimize the power losses and maximize the main grid load factor.

The penetration of EVs may bring potential challenges to electric utility especially at the distribution level. The conclusion of reference [10] indicates that the load created by PHEVs in some cases may exceed the distribution transformer capacity. Reference [11] proposes a comprehensive approach for evaluating the impact of different levels of PHEV penetration on distribution network investment and incremental energy losses.

V2G mode EVs can exchange energy with the power grid. However, the previous references only focus on characteristics study of the charging load without considering the discharging process. While in reference [12] [13], the authors investigate different charging strategies for EVs with respect to their impact on the local power distribution network of a residential area. They assess the optimal car battery dis/charging scheduling to achieve peak shaving, reduction of the variability (over time) of the load, and cost reductions for electric mobility, respectively.

The aim of this paper is to model different kinds of EV loads by considering most of the impact factors on regional EV load. Then this paper will simulate the impact of different EV models and different EV scales on the grid based on the grid load curve of a real district in China.

The rest of this paper is organized as follows. Section II describes the impact factors on V2G EVs performance being as regional loads in this study. In section III, Three kinds of EV load models are built and simulated. Simulation results of the influence of EVs on the power grid are then presented and discussed in section IV. Finally, conclusions are given in section V.

II. IMPACT FACTORS ON V2G EVS PERFORMANCE BEING AS REGIONAL LOADS

There are many types of EVs. They can be divided into 3 categories in China: 1) Group vehicles. This includes buses for public transportation, street sweepers, garbage trucks,

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water trucks for sanitation departments, postal delivery vehicles for postal departments, electrical engineering vehicles for power utilities, etc. This type of EVs has the features of regular driving route and fixed parking lot. 2) Social vehicles. This includes official cars, business cars, and taxis and so on. The feature of this type is that driving route is strongly random and has a large radius. 3) Private vehicles. This type of vehicles has great randomness and short driving distance. As a V2G EV, it should have short driving distance and long parking time, plenty of time and capacity interact with the grid as well. In a word, V2G EVs are most suitable for private vehicles.

The most crucial impact factors on V2G EVs performance being as regional loads are the battery capacity, the single EV charging and discharging power, user behavior, and initial battery charge state, the scale of EVs [14][15]. Some of them, such as the battery capacity, the single EV charging and discharging power, the scale of EVs, may be acquired in advance. While the user behavior and initial charge-discharge state is random, those cannot be obtained beforehand. Therefore, the study on characteristics of EV charging and discharging load should take full account of these factors.

The user behavior is determined by two aspects, which are the start time of battery charging or discharging and the daily driving distance. Private vehicles are mainly used for work and leisure activities, and the location where to charge or discharge is probably at home or workplace. The time interval for discharging or charging is probably from reaching the workplace in the morning to punching out in the afternoon and from arriving at home in the afternoon to leaving home to go to work in the next morning. According to the working time in enterprises and government institutions in China, the probable charging and discharging time intervals are 9:00-17:30 and 19:00-7:00. According to the user behavior, most people would start to charge or discharge soon after arriving at home or workplace. The start charging or discharging time is closed to normal distribution and its probability density function is as follows:

$$f_{s1}(x)=\frac{1}{\sigma_{s1}\sqrt{2\pi}}\exp\left[-\frac{(x-\mu_{s1})^2}{2\sigma_{s1}^{\ 2}}\right] \tag{1}$$

where, μ_{s1}=9； σ_{s1}=0.5

$$f_{s2}(x)=\frac{1}{\sigma_{s2}\sqrt{2\pi}}\exp\left[-\frac{(x-\mu_{s2})^2}{2\sigma_{s2}^{\ 2}}\right] \tag{2}$$

where, μ_{s2}=19； σ_{s2}=0.5

According to the survey of national household vehicles by U.S. Department of transportation in 2001, the daily mileage can be approximately log-normal distribution using the maximum likelihood estimation [16]. Its probability density function is as follows:

$$f_D(x)=\frac{1}{x\sigma_D\sqrt{2\pi}}\exp\left[-\frac{(\ln x-\mu_D)^2}{2\sigma_D^{\ 2}}\right] \tag{3}$$

Where, μ_D=3.5； σ_D=0.91

The daily mileage reflects the daily power consumption, and is related to the state of charge (SOC) of the EV battery. The initial SOC of an EV battery can be expressed as

$$soc_0=(1-\frac{\alpha d}{d_R})\times 100\% \tag{4}$$

Where, α is the number of traveling days, here is 1. d is the daily mileage. d_R is the maximum range of the EV, and the typical value for d_R is 80 miles [7].

Under given charging or discharging power, the active duration is related to initial battery SOC and final battery SOC. For analysis convenience, without considering the charging-discharging efficiency, the battery temperature, the change of voltage, the cycle times of battery charge/discharge, the charging or discharging duration is shown as follows:

1. The charging duration,

$$t_c=\frac{(soc_c-soc_0)}{r_{ci}} \tag{5}$$

Where soc_c is the final battery charging SOC. When the battery is fully charged, $soc_c=1$. r_{ci} is the charging current. For a battery with 1C rated capacity, assume charging at 0.1C and 0.2C charge current, the battery charge duration from empty to full is 10h and 5h, respectively.

2. The discharging duration,

$$t_d=\frac{(soc_0-soc_d)}{r_{di}} \tag{6}$$

Where soc_d is final battery discharging SOC. In order to improve the battery life, the minimum soc_d is 0.1. r_{di} is the discharge current. For instance, if a battery with 1C rated capacity is discharged respectively at 0.1C and 0.2C discharge current, the battery discharge duration from full to empty is 10h and 5h.

III. MODELING OF THE REGIONAL EV LOAD

The scale of electrical vehicle in a particular region is certain. The total daily EV load curve can be obtained by accumulating all EV loads in this region. The minimum time interval is in minute, and 1440 mins in a day is covered. The region EV load at each minute can be expressed as:

$$P_{Ti}=\sum_{n=1}^{N}P_{n,i} \tag{7}$$

Where, P_{Ti} is the total EV load power at the *ith* min, $i=1,2,\ldots,1440$; N is the number of EVs in the area. $P_{n,i}$ is the *nth* EV load power at the *ith* min.

The V2G EV can not only acquire energy from the grid and can also transfer energy to the grid. According to whether it transfers energy to the grid and whether it is controlled by the tariff structure, three EV load models are built.

1. Model 1-Uncontrolled charging model(UCM): without transferring energy to grid, and uncontrolled by tariff structure, the EV is randomly charged by the user.
2. Model 2-Controlled charging model(CCM): without transferring energy to grid, but controlled by tariff structure, the EV is charged when the grid load is in off-peak period.
3. Model 3-Controlled charging/discharging model (CCDM): transferring energy to grid, and controlled by tariff structure, the EV is charged during the off-peak period and discharged during the on-peak period. This can achieve the goal of the smart power management.

Time of use (TOU) electricity pricing divides one day into different time intervals according to the characteristics of the load curve, and different electricity prices are assigned to different time intervals. Different regions may have different period divisions.

In this paper we adopt the period divisions by Shandong power grid in China. The whole day is divided into three periods, two peak periods, one off-peak period and two flat periods. The peak periods includes the morning peak (8:30-11:30) and the evening peak (18:00-23:00). The off-peak period is defined as 23:00-7:00. The flat periods consist of the time intervals of 7:00-8:00 and 11:30-18:00.

For the Model 1 EV, the mean of its daily mileage distribution is 3.2 miles and the standard deviation is 0.88. The start charging time is at any time which meets one of the two kinds of normal distributions, N (9, 0.5) and N (19, 0.5). The process of the regional EV load calculation using Monte Carlo simulation for Model 1 EVs is shown in Fig.1. The system generates a random number, which meet U (0, 1) uniform distribution, to stand for the probability of two charging periods, and use binomial distribution to determine the start charging time for a single vehicle.

For the Model 2 EV, the daily driving mileage is the same as the Model 1 EV, the start charging time is set as 23:00. The process of the regional EV load calculation using Monte Carlo simulation for Model 2 EVs is shown in Fig.2.

The Model 3 EV has a power exchange with the grid. It is often charged at peak period and discharged at off-peak period. Since it is assumed there are two peak periods and one off-peak period, the EV can be discharged twice and charged once in a day. The morning driving distance is half of the daily mileage, and the EV could offer power to grid if the battery SOC is higher than 0.5. After discharging at the morning peak period, the SOC of battery should not be lower than 0.5 in order to guarantee continual driving. The battery SOC of evening peak discharging is determined by the daily mileage and the morning peak discharging power. The start discharging time is 8:30 and 18:00. It is assumed that the battery was empty after twice discharges. The minimum value of SOC is 0.1. After that, the battery will be charged at 11:00. Fig. 3 shows the flowchart of the algorithm.

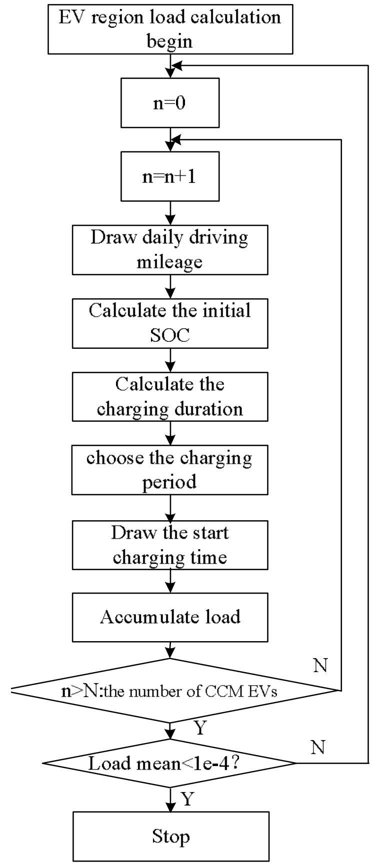

Fig. 1 The flowchart of the regional EV load calculation for Model 1 EVs

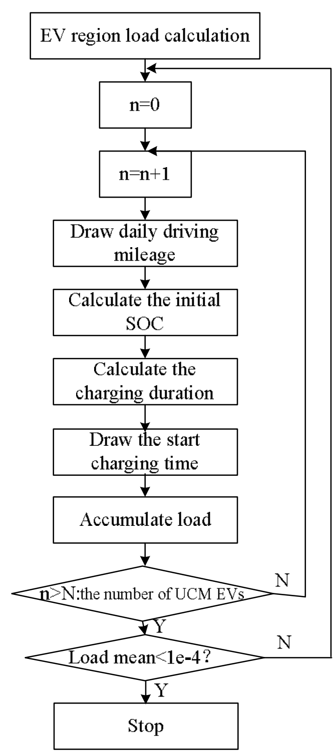

Fig. 2 The flowchart of the regional EV load calculation for Model 2 EVs

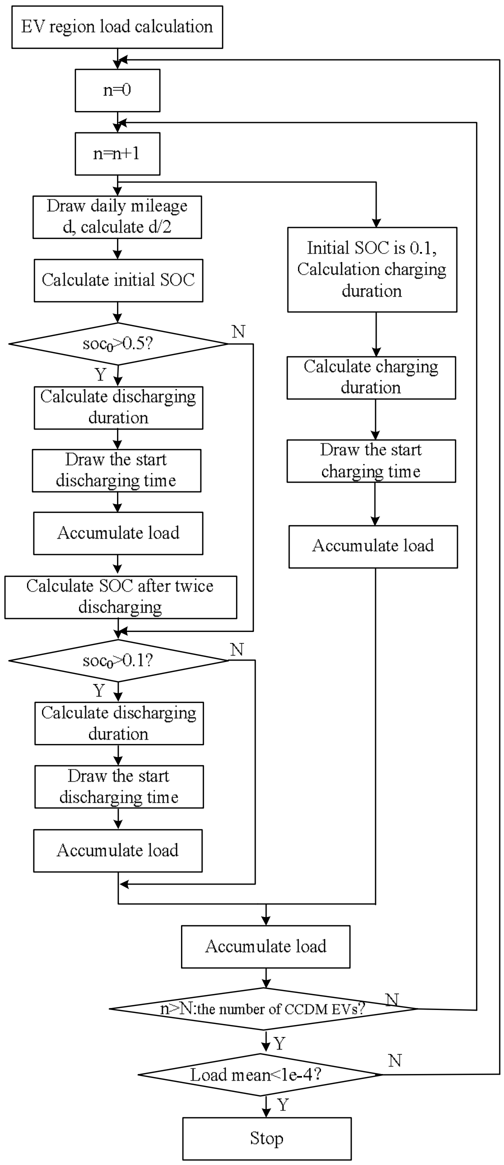

Fig. 3 The flowchart of the regional EV load calculation for Model 3 EVs

IV. CASE STUDY

This paper adopts Monte Carol simulation algorithm. The first step of the algorithm is to produce the daily mileage and the start charging or discharging time of each EV. As mentioned above, the initial SOC and the charging-discharging duration will be calculated by using equation (4) (5) (6). After determining the state of the EV, the regional EV load can be obtained. The convergence tolerance is set 1e-4.

We choose Qingdao Economic and Technological Development Zone (QETDZ) in Qingdao city, Shandong Province as an example to analyze the impact on the grid of different regional EV load models. According to the data from National Bureau of Statistic of China published in 2010, there are 25 cars per thousand persons in China. The population of QETDZ is 524.2 thousand, so it can be estimated that there are 13,105 private cars in this area. Assuming 35% of these cars are EVs, then the number of the EVs in QETDZ is 4,587. There are different types of EV battery, in this paper a common lithium-ion battery is chosen, of which rate voltage is 320V and the rated capacity is 100A • h. The original daily load curve of the QETDZ power grid without EVs is shown in Fig. 4.

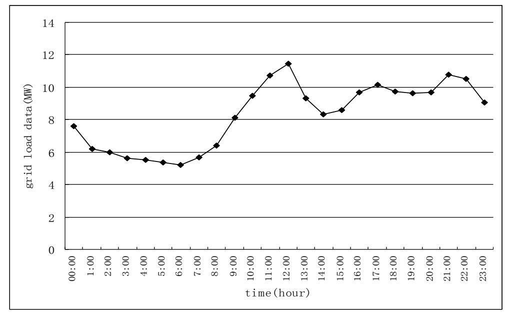

Fig. 4 The daily load curve without EVs

Under given charging/discharging power, the impact of three EV load models on the grid load curve is presented in Fig.5.

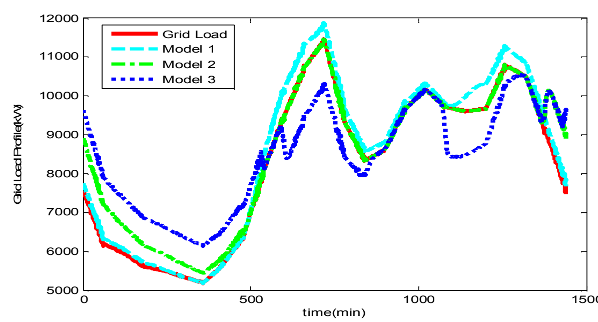

Fig. 5 The impact of three EV load models on the grid load curve

The impact of three EV models on the load rate and peak-valley difference of the grid is shown in Table 1.

TABLE 1. THE IMPACT OF THREE EV MODELS ON THE GRID LOAD RATE AND PEAK-VALLEY DIFFERENCE

	Grid load	**Model 1**	**Model 2**	**Model 3**
Load rate	71.9%	72.21%	74.25%	80.31%
Peak-valley difference (kW)	6284.8	6665.3	6026.6	4383.6

It can be seen from Fig. 5 and Table 1 that, for model 1, the disorderly EV charging would increase the peak-valley difference of the grid because the EV charging time is often during the grid peak-valley period and will bring a new load burden on the peak load regulation pressure for the grid. For model 2, the controlled charging for EVs increase the grid load rate from 71.9 to 74.25, and reduce the peak-valley difference from 6284.8kW to 6026.6kW. For model 3, the grid load rate has improved effectively and the peak-valley has dropped off. In a word, the orderly management of discharging/charging for EVs is an effective method to cut peak load shifting. Therefore it can improve load factor and economical operation of the grid.

Regional EV loads have a certain relationship with the scale of EVs. The impact of different scale of EV on the grid is different. Under given charging/discharging power, the influence of three kinds of EV models is shown in Fig. 6, Fig.7 and Fig.8. The size of EV which participates in V2G energy exchange is 10%, 20%, 50%, respectively.

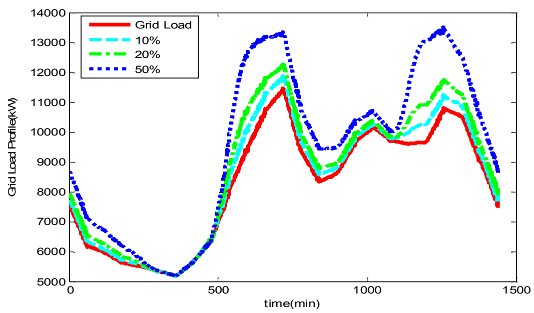

Fig. 6 The impact of model 1 EV in different scales on the grid load curve

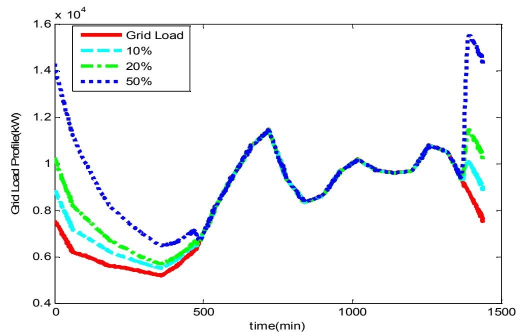

Fig. 7 The impact of model 2 EV in different scales on the grid load curve

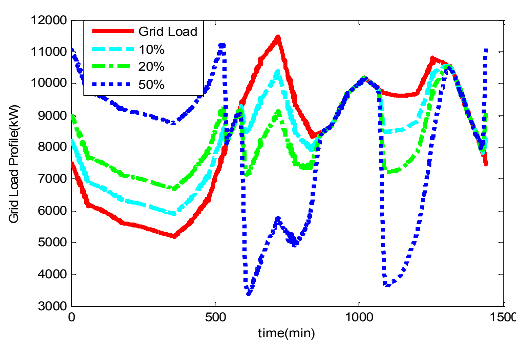

Fig. 8 The impact of model 3 EV in different scales on the grid load curve

Fig. 6 shows that, under any circumstances, the disorderly energy exchange will increase the peak-valley difference. It can be seen from Fig. 7 and Fig. 8, under a certain EV scale, the orderly energy exchange between EVs and the grid is helpful to improve the load balance in power systems. However, if the EV scale exceeds a certain level, it will increase the peak-valley difference and influence the load balance in the power grid. Therefore, the scale of EVs which take part in energy exchange between the gird and EVs should have a limit.

V. CONCLUSION

This paper presents a methodology to determine the regional EV load. Three kinds of EV load models are built and simulated including uncontrolled charging model, controlled charging model and controlled charging/discharging model. The impact of three different EV load models on the grid load curve and on the load rate and peak-valley difference of the grid is presented. And the impact of different scale of EVs on the grid is also discussed. The simulation results show that the model 1 EV is the worst case in terms of peak power demand, no matter the scale of EV is large or small. Model 2 and Model 3 EV are helpful to reduce the peak-valley difference and raise the grid load rate. However, the number of EV should not exceed a certain level. The Model 3 EV is better than Model 2 EV since the former can be scheduled optimally to exchange energy with the grid.

This paper only addresses the influence of different kinds of EVs on the grid load profile and does not take the structure of the power grid into consideration. The future work will discuss the influence of EVs at different locations on the power gird considering the network structure of the grid.

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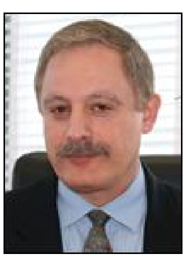

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