Optimization of Orderly Charging/Discharging Strategy for Electric Vehicles Considering Incremental Cost of V2G

Saier Yu[1,*], Yiyu Huang[2], Yang Chen[1]

[1] Xi'an Jiaotong University, School of Electrical Engineering, Xi'an, Shaanxi, China
[2] Central Southern China Electric Power Design Institute, Wuhan, Hubei, China

Abstract. The integration of electric vehicles (EV) into demand-side response holds significant potential, which not only helps to reduce the operational expense of EVs, but also presents a viable strategy for the grid peak regulation. In this paper, the load simulation model of EVs is proposed based on the probability distribution of charging/discharging behaviours of different types of EV users from statistical data. On this basis, considering the incentive effect of hourly electricity price, an orderly charging/discharging optimization model is proposed to consider EV charging cost, discharge income and incremental battery loss cost caused by EV participating in the vehicle-to-grid (V2G) mode. This model provides a more accurate estimation on the incremental costs and market arbitrage benefits of EVs in V2G mode on the basis of conventional transportation utilization, so as to better optimize the operation strategy of the EVs for demand response. Numerical results show that in the context of tariff of usage (TOU), the orderly charge and discharge model reduces the operating cost of EV users, and can better exploit the potential of EV energy storage batteries in power grid peak regulation.

1 Introduction

Carbon emissions of China's power energy and transportation industries have reached 47.4% and 7.5% of total respectively, accounting for more than half of the country's CO_2 emissions [1]. Therefore, the requirement of low-carbon transformation of transportation energy has become an urgent problem to be solved, with a key technological path of vigorously developing electric vehicles (EV). However, the integration of large-scale unordered EV charging brings adverse effects to the power grid, such as dramatically increased peak-to-valley load difference and uncertainty of EV charging loads, leading to decreased power quality [2]. To better guide the travel demand and charging demand of EV is hence the basic work to realize the cooperative operation of power grid and traffic under the scenario of large-scale EV integration to the power grid, considering the basic traffic function of EV.

At present, the research on EV charging load distribution mainly starts from EV operating mode, and is carried out through the correlation between characteristics of travel traffic, electric energy consumption and charging load. Literature [3-4] analyzed the travel characteristics of EV users and predicted the charging load of EV based on the mapping relationship between travel mileage and power consumption. Based on the analysis of EV staying area and charging behavior, literature [5-6] obtained the distribution characteristics of EV charging load in different zones, and proposed an EV charging load prediction model based on EV driving behavior and parking characteristics. In literature [7], big data-related technologies were used to establish prediction models based on traffic and weather data, and classification standards were established by decision tree to predict EV charging demand on different date types. The above literatures have made a beneficial exploration on the load demand prediction and characteristics of EVs.

Under the power market environment, bringing in time-of-use (TOU) electricity price can guide the power users to implement demand-side response and peak load shaving and shifting. Since the EV is itself an energy storage battery, it is easier to change the charging behaviour, respond well to price changes, and achieve an orderly charging/discharging strategy. Based on the TOU strategy, literature [8-9] guided EV to participate in the power balance of the system by constructing a minimum charging cost model of EV. Literature [10] put forward the overall structure of V2G management system, and adopted fuzzy control algorithm to calculate charging/discharging power, and sent it to each charging pile to improve the load characteristics of regional power grid. Literature [11] established a multi-objective cooperative scheduling model with the objectives of minimizing the mean square error of the system load curve and minimizing the user's electricity cost. Literature [12] proposed a two-stage multi-objective optimization model solution method and an orderly charging control strategy based on multi-population genetic algorithm. In the first stage, Monte Carlo

* Corresponding author: 2204224988@stu.xjtu.edu.cn

simulation was introduced to EV charging behaviour and transformation of the charging load from the peak period to the normal period or the off-peak period. In the second stage, error prediction was used to further optimize the charging load during the peak period. Besides, EV participating into the V2G mechanism of demand-side response will increase the cost of battery life loss and charging facility upgrading. However, to the best of our knowledge, abovementioned studies have not considered the impact of this cost on EV charging and discharge optimization.

In this paper, the charging behaviours of individual EV users are categorized into three types assigned with different probability distribution characteristics of the travel plans. Then, applying Monte Carlo simulation, the load of EV groups in the charging pool is modelled. Based on the load estimation of the EVs, an optimization model of EV charging/ discharging strategy is proposed to minimize the EV operation costs under TOU as well as the battery loss cost of EVs, taking into account the economic benefits and increased interactive losses of vehicle owners participating in the demand-side response of the grid. Then, followed by a thorough numerical analysis, the impact of charging modes of EVs and the price setting of TOU mechanism on the grid peak regulation is discussed.

2 Analysis of EV charging/discharging characteristics based on traffic behavior

The influencing factors of EV load mainly include EV behavior state and battery state. The behavioral state of EVs depends on the user's travel habits, mainly including charging, driving, parking, and so on.

In this paper, pure electric private cars are taken as the research object, with following assumptions on charging behavior of EVs as the boundary conditions:

• The operation duration is set as 1 day, divided into 96 sub-periods, each for 15 minutes.

• Considering the physical characteristics of the EV battery, assuming that the state of charge (SOC) of the EV in the charging pool is 20%-100%;

• Because the function of EVs on weekdays is mainly for commuting, the electricity consumed can be made up at relatively short time, assuming that the expected number of times for each EV charging is only once a day.

2.1 Daily electricity requirement

For electric private cars, it is mostly used for commuting to and from work on weekdays, and the travel path is relatively fixed, so the driving mileage can be set according to the commuting distance [13]. Assuming that EV travel distance on working days follows a lognormal distribution, that is, $S\sim Log\text{-}N(\mu_S,\sigma_S^2)$, and the probability density function (PDF) is shown in equation (1).

$$f_s(x)=\frac{1}{x}\frac{1}{\sigma_s\sqrt{2\pi}}\exp\left(-\frac{(\ln x-\mu_s)^2}{2\sigma_s^2}\right) \tag{1}$$

Where, μ_S、 σ_S are the mean and variance of a lognormal distribution respectively.

The distribution parameters in equation (1) can be obtained by fitting the commuting distance data based on the *Commuter Monitoring Report of Major Cities in China 2022*. Statistical analysis shows that different city size will lead to different parameter ranges.

The EV daily charge E_{need} can be obtained based on EV mileage and energy consumption per kilometer (km), and the energy consumption per km can usually be acquired by means of endurance mileage and battery capacity of EV.

2.2 EV charging/discharging time

2.2.1 Charging start moment

The charging start moment of EV mainly depends on the working mode of EV. By analyzing the daily driving distance and EV parameters, it is concluded that most of daily EV consumption can be filled in a short time. From the perspective of mathematical analysis, it can be considered that the EV involved in charging is only charged once a day [14]. Therefore, EV users are classified into three types according to the start/end charging moment:

- Type 1 owners often start charging immediately after returning home from work, and finish charging when they go to work the next morning.

- Type 2 will charge at the workplace after arriving at office in the morning and finish charging after work.

- The charging start/end moment of type 3 owners is not fixed.

The start/end charging moment of the above three type owners was modelled respectively. It is considered that the start charging moment T_{start} of the first two types follows a normal distribution $N(\mu_{\mathrm{TS}},\sigma_{\mathrm{TS}}^2)$, while the start charging moment of the 3rd type follows a uniform random distribution $U(0, 96)$. The PDF of the moment when each type of car owners start charging is shown in formula (2) and (3).

$$f_{Tstart,j}=\begin{cases}\dfrac{1}{\sigma_{\mathrm{TS},j}\sqrt{2\pi}}\exp\left(-\dfrac{(x-\mu_{\mathrm{TS},j})^2}{2\sigma_{\mathrm{TS},j}^2}\right),(\mu_{\mathrm{TS},j}-48)\le x\le 96\\ \dfrac{1}{\sigma_{\mathrm{TS},j}\sqrt{2\pi}}\exp\left(-\dfrac{(x+96-\mu_{\mathrm{TS},j})^2}{2\sigma_{\mathrm{TS},j}^2}\right),0\le x<(\mu_{\mathrm{TS},j}-48)\end{cases} \tag{2}$$

$$f_{Tstart,3}=\frac{1}{96} \tag{3}$$

Where j=1, 2, indicates car owners of type 1 and 2. μ_{TS}, σ_{TS} are the mean and variance of the moment distribution for start charging respectively.

According to the statistical data in literature [13], the mean value and standard deviation can be $\mu_{\mathrm{TS},1}$=76, $\mu_{\mathrm{TS},2}$=36 ; $\sigma_{\mathrm{TS},1}$=6,,$\sigma_{\mathrm{TS},2}$=4. In addition, it is believed that type 1 owners account for 60%, while type 2 and type 3 owners account for 20% respectively.

2.2.2 Distribution for available charging/discharging time

In order to gain the charging/discharging time, firstly we must calculate the charging end moment T_{end}. On the basis of T_{start}, add the charging duration T_{con}, that is, T_{end} is obtained, but there will be cross-day situations (that is, $T_{start}+T_{con}>96$). Since the charging/ discharging strategy of private cars in working days is the object of study, the EV travel rules of two consecutive working days and the base load curve of the object area are consistent, so the sub-period beyond the 96th period is placed at the beginning of the first period (as the next day) in this paper. The calculation of T_{end} can be obtained as shown in formula (4).

$$T_{end}=\begin{cases} T_{start}+T_{con}, & T_{start}+T_{con}\le 96 \\ T_{con}-\left(96-T_{start}\right), & T_{start}+T_{con}>96 \end{cases} \tag{4}$$

Therefore, the distribution for available charging/ discharging time can be divided into two cases according to whether it is cross-day or not, as shown in Figure 1.

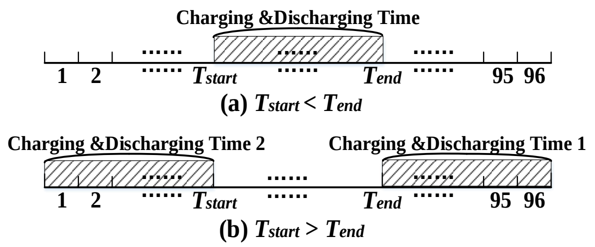

Fig.1 Distribution for available charging/discharging time

2.2.3 Initial state of charging (SOC) for EV

According to literature [15], the SOC of EV at the right beginning, that is, the initial SOC, follows a normal distribution $N(\mu_{SOC}, \sigma_{SOC}^2)$. Suppose the mean μ_{SOC} =0.5 and the variance σ_{SOC} =0.1, then the probability density function of the initial SOC is shown in equation (5).

$$f_{soc}=\frac{1}{\sigma_{soc}\sqrt{2\pi}}\exp\left(-\frac{\left(x-\mu_{soc}\right)^2}{2\sigma_{soc}}\right) \tag{5}$$

3 Monte Carlo simulations on charging/ discharging scenarios of EV

Monte Carlo simulation (MCS) is a method of data generation based on probabilistic statistical theory that relies on repeated random sampling to obtain numerical results. MCS can be divided into two steps, ie, constructing the probability distribution of the random variable to be simulated and generating the sample values conforming to the distribution [16-17]. Among them, the construction of a probability distribution that can truly reflect the characteristics of random variables is the basis of simulation. The modelling in section 1 has led to the probability distribution model of EV's required charging amount E_{need}, charging start moment T_{start}, charging end moment T_{end}, and initial charging state SOC_{start}.

After the charging start/end moment of each EV cluster in a certain region is determined by Monte Carlo method, the total load caused by EV users in the region at every moment of the day is calculated as the sum of the charging load of each EV at this moment. The total charging load of the region is set as *P*, then the calculation for *P* is shown in equation (6).

$$P_{S,t}=\sum_{i=1}^{N_{\mathrm{EV}}}P_{i,t} \tag{6}$$

Where, N_{EV} represents the number of private cars charged in the area in a day. $P_{S,t}$ and $P_{i,t}$ respectively represent the total charging power and the charging power of certain electric private cars (the amount of cars is *i*) in the area at the moment *t*.

4 EV charging/discharging optimization model considering V2G

Under the electricity market environment, EV users can use the power supply capacity of their storage batteries in cars to participate in the demand-side response of the grid, that is, charging at low electricity prices and discharging during high electricity prices (V2G), and obtain arbitrage benefits on the basis of reducing electricity costs. The V2G behaviour of EV users will increase the number of charge and discharge cycles of energy storage batteries, causing additional battery life loss, and this part of the incremental cost of V2G battery loss is also the core factor that owners must consider when developing charging/discharging strategies.

4.1 Objective function

On the premise of meeting the driving power demand, the goal of EV user's charging/discharging decision is to obtain the minimum comprehensive cost after charging cost, incremental loss cost minus discharge income, as shown in equation (7).

$$\min F_i=\sum_{t=1}^{96}\left(\frac{P_{i,t}^{Chr}\cdot r_t-P_{i,t}^{DChr}\cdot r_t}{4}+C_{i,t}^{BAT}\right) \tag{7}$$

Where, F_i is the comprehensive cost of the i^{th} EV, and the charging/discharging power of the i^{th} EV at the moment *t* respectively. r_t is the electricity price at moment *t*. $C_{i,t}^{BAT}$ indicates costs of incremental battery loss due to V2G.

Studies have shown that in the process of EV charging/ discharging, the battery loss will occur [18], and then the battery loss cost will be counted. Literature [19] points out that the life of EV batteries and the number of charging/discharging cycles is roughly in linear decline relationship. The cycle periodic-life relationship curve of traditional lithium iron phosphate ($LiFePO_4$) batteries commonly used in EV [20-21] is shown in Figure 2. If the capacity of EV vehicle battery drops below 80%, it will have a great impact on normal use, and the battery needs to be replaced. By referring to the curve shown in Figure 2, the number of cycles corresponding to the actual effective EV battery capacity can be obtained.

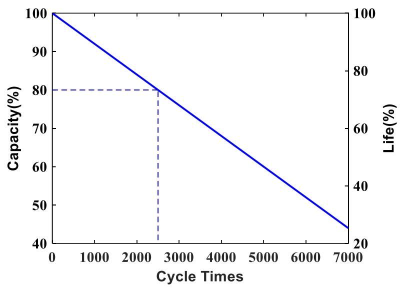

Fig.2 Cycle times-life curve relationship of traditional lithium iron phosphate battery

Since the incremental battery loss cost $C_{i,t}^{BAT}$ caused by V2G is mainly determined by the discharge to the grid, discharge efficiency and the actual number of cycles, calculation of $C_{i,t}^{BAT}$ is shown in formula (8) and (9).

$$E_{i,t}^{flow} = \frac{1}{4} \times P_{i,t}^{DChr} \Big/ \beta \tag{8}$$

$$C_{i,t}^{BAT} = \frac{E_{i,t}^{flow}}{0.8E_i^N} \times \frac{c^{BI}}{LC_i} \tag{9}$$

Where, $E_{i,t}^{flow}$ is the charge amount required by the i^{th} EV due to discharging to the grid, kWh. β is the charge and discharge efficiency. E_i^N is the rated battery capacity of the i^{th} EV. c^{BI} is the EV battery replacement cost, usually including battery manufacturing costs and labor costs. LC_i is the rated cycle life of i^{th} EV battery. The division by 4 in equation (8) corresponds to the division of an hour into four sub-periods in this paper.

Under the incentive of TOU pricing policy in the power market, EV will try to charge in the low price period and discharge in the peak price period in order to pursue individual interests, so as to achieve the effect of peak cutting and valley filling required by the system.

4.2 Constraint condition

4.2.1 Charge and discharge state mutually exclusive constraints

The charging and discharging states of EV cannot occur at the same time, that is, at least one of EV charging power and discharging power is zero at a certain time

$$P_{i,t}^{Chr} * P_{i,t}^{DChr} = 0 \tag{10}$$

4.2.2 Available charging/discharging time constraint

EV can only be charged and discharged within the available charging/discharging time mentioned in section 1.2.2. In the period other than the available charging/discharging time, EV battery should be charged and discharged at zero power to restrict the charging and discharging power

$$\begin{cases} P_{i,t}^{Chr} = 0 \\ P_{i,t}^{DChr} = 0 \end{cases} t \in \begin{cases} (T_{end}\ , 96] \cup [1\ , T_{start})\ , T_{\text{start}} \le T_{end} \\ (T_{end}\ , T_{start})\ , T_{\text{start}} > T_{end} \end{cases} \tag{11}$$

4.2.3 Charging amount constraint

It is necessary to ensure that after the whole charging / discharging process, the charging amount of EV is not less than the electric power required by EV E_{need}, and the amount of charging/discharging is restricted as below

$$\frac{\beta \times (P_i^{in} \times \sum x_{i,t}^{pos} + P_i^{out} \times \sum x_{i,t}^{neg})}{4} \ge E_{need} \tag{12}$$

4.2.4 Battery SOC constraint

In order to ensure the safety of EV batteries, it is also necessary to limit the discharge depth of the battery, and to prevent the battery from over-charging and over-discharging. So the battery SOC is restricted as

$$SOC_{\min} \le SOC_{i,t} \le SOC_{\max} \tag{13}$$

Where, $SOC_{i,t}$ is the charged state of the i^{th} EV after the end of the No. t sub-period. SOC_{max} and SOC_{min} are the maximum and minimum charge states of the battery respectively.

5 Analysis of examples

5.1 Parameter setting

In order to verify the effectiveness of the EV charging/discharging strategy proposed above, BYD e2, one of the most popular EV type with the highest market share, is adopted in the analysis. Its rated battery capacity E^N =43.2kWh. Rated charging power P^{CHr} = 6.6kW. Rated discharge power P^{DCHr}= 3.3kW. Mileage for one kWh is 9.375km/kWh. The replacement cost of $LiFePO_4$ battery c^{BI} is ¥45,000. Battery cycle life is 2500 times. Charge and discharge efficiency β is set to 0.9. The commuting distance follows *Log-N*(2.3, 0.88^2).

It is assumed that the study area contains a total of 1000 private EVs, and the base load distribution of typical days in this area is shown in Table 1. The base load of 96 sub-periods is obtained through mathematical fit. The general industrial TOU price is shown in Table 2[22].

Table 1. Basic load of a day

Moment	Load/MW	Moment	Load /MW	Moment	Load /MW
1:00	23.89	9:00	27.15	17:00	29.02
2:00	23.61	10:00	28.63	18:00	30.01
3:00	23.08	11:00	31.38	19:00	31.19
4:00	22.79	12:00	32.23	20:00	32.95
5:00	24.03	13:00	31.96	21:00	31.96
6:00	25.13	14:00	30.73	22:00	29.80
7:00	25.92	15:00	30.10	23:00	26.36
8:00	26.87	16:00	29.26	24:00	24.03

Table 2. TOU price

Period type	Period division		Price(¥/kWh)
Peak	10:00-15:00	18:00-21:00	1.322
Normal	7:00-10:00	15:00-18:00	0.832
	21:00-23:00		
Valley	23:00-7:00		0.369

5.2 Analysis of example results

5.2.1 Analysis of peak regulation effect of orderly charging

In order to analyse the impact of different charging strategies on EV users and power system load peaking, three EV charging/discharging modes are simulated in this paper:

- The unordered charging mode is adopted.

- Orderly charging under the TOU price (referred to as Orderly mode).

- Under the TOU price, together with ordered charging mode including V2G (referred to as V2G mode).

The charge and discharge curve of EV cluster is superimposed on the base load, and the total load curve of the system obtained including EV is shown in Figure 3, and the technical and economic results are shown in Table 3.

Table 3. Characteristic of curve and total cost

Charging mode	Peak-valley difference rate %	Charging cost/¥	Discharge earning/¥	Incremental loss cost/¥	Total costs /¥
Unordered	35.14	3152	/	/	3152
Orderly	25.79	2646	/	/	2646
V2G	23.08	6429	10359	5508	1578

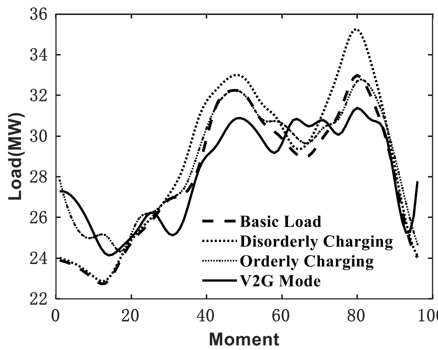

Fig.3 Load curves of different charging modes

As can be seen from Fig. 3 and Table 3, if EV users adopt the random charging mode upon arrival at the parking place, the peak-valley difference of the total system load increases after EV load is added, while the two orderly charging modes both reduce the peak-valley difference of the total load. Especially for V2G mode, compared with the peak-valley difference rate of 30.83% of the base load, the decrease ratio is as high as 25.1%, which significantly reduces the demand for peak regulation of the system.

From EV user's perspective, the combined total cost for EV users with V2G mode is the lowest, which reduces the total cost by 49.9% comparing to unordered charging mode. From the perspective of cost composition, the V2G mode increases the charging cost and battery loss cost by 104%. However, because EV discharge to the system during the peak electricity price period can obtain up to 2.74 times the income from electricity sales, which is much higher than the cost increment, making the comprehensive cost of EV users greatly reduced. Therefore, under the condition of TOU tariff, guiding EV users to participate in V2G can benefit both grid and EV users.

5.2.2 Effects of different electricity pricing mechanisms on EV charging/discharging strategy and load

In order to analyze the influence of different electricity pricing strategies on EV charging/discharging load curve and the peak-valley difference of the total system load, three different peak-valley electricity pricing ratios were set for calculation and analysis. It is assumed that all EVs in this region participate in the ordered charging/ discharging of V2G. Three different pricing strategies for peak period are selected in this paper (scene settings are shown in Tab.4) to optimize V2G charging/ discharging strategies for EV. The calculation results are shown in Table 4.

Table 4. Different peak and valley time price

Scene setting	Period price			Peak-valley ratio
	Normal	Peak	Valley	
Scene 1	0.832	1.322	0.369	3.6
Scene 2	0.832	1.082	0.6	2.16
Scene 3	0.832	1.664	0.29	5.71

The daily total load curve under the three scenarios is shown in Fig. 4, and the peak-valley difference ratio and various costs are shown in Table 5.

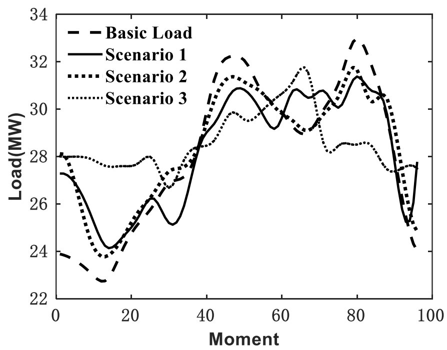

Fig.4 Load curves of different peak and valley time price

Table 5. Characteristic of overall load and costs (different peak - valley time price)

Price strategy	Peak-valley difference rate %	Charging cost/¥	Discharge earning/¥	Incremental loss cost/¥	Total costs /¥
Scene 1	23.08	6429	10359	5508	1578
Scene 2	25.16	3903	4028	2507	2382
Scene 3	16.02	6862	14670	7257	-551

As can be seen from Fig. 4 and Table 5, in scene 1, EV will choose to charge at valley and normal hours and discharge at peak hours within its available charging/ discharging time, thus completing the arbitrage, showing a good peak cutting and valley filling effect.

In scene 2, as the electricity price in peak and valley periods is closer to the electricity price in normal periods, for some EVs with limited charge-discharge time (for example, the available charge-discharge time is mostly distributed in the valley and normal periods), taking into account the existence of battery loss costs, the benefits of participating in V2G may be less than the cost of accelerating battery loss caused by frequent charge-discharge. Therefore, for such EVs, Most of them only charge in the low period as far as possible to achieve their own charging requirements, and will not participate too much in V2G, so the total cost of scene 2 is higher than that of scene 1, and the effect of peak clipping and valley filling is also worse than that of Scene 1.

For scene 3, contrary to scene 2, the benefit brought by most EVs participating in V2G is significantly greater than the incremental battery loss cost brought by this behaviour due to the more obvious difference in electricity prices between peak and valley periods. Users are motivated by high payback and switch to V2G state in more periods, so the peak-load shifting effect of base load is better. However, it is noted that in some parts of the curve, such as the 60-68th period (corresponding to 15:00-17:00), there is a new small load peak. This phenomenon is mainly due to the fact that from 15:00, the electricity price changes from high electricity price to flat electricity price. For the type 2 car owners mentioned in section 1.3 who choose to charge after arriving at the work place, Its EV will start charging on a large scale at 15:00, and the base load itself is not low during this period, it will form a new load peak, until 17:00 as most owners finish charging after work, the load will start to reduce). Therefore, when the ratio of peak-valley electricity price increases to a certain extent, EV participation in V2G may lead to excessive peak-load shifting, resulting in new load peaks and new impacts on the power system.

Through the above analysis, it can be concluded that with the increase of electricity price backing during peak/valley period, EV can be encouraged to optimize its own charge and discharge strategy and participate more in V2G for arbitrage, which plays a better role in peak-load shifting for the load curve of the whole region. However, if the price gap between peak and valley is too large, it will not only increase the V2G subsidy expenditure of power suppliers, but also may form a new load peak, which will have an adverse impact on the power system. Therefore, it is necessary to set the peak, flat and valley electricity price reasonably.

Because participating in V2G will make the charging method of the owner more complicated, and although the BYD e2 car selected in this paper has the discharge function, not all kinds of EV on the market have this function, so the concept of V2G response rate α is introduced here. Response rate α is a parameter between 0-1, indicating the proportion of EV in response to V2G selected in the region. For EVs that do not participate in V2G, a disorderly charging method is adopted (that is, EV is charged at rated power when it is connected to the grid to start charging, and will be stopped when the charging requirement has been reached).

The time-sharing pricing strategy in Table 2 was selected to simulate the 100% response rate, 60% response rate, 30% response rate and 0% response rate (i.e., unordered charging) respectively. The daily load curves under different response rates were obtained as shown in Fig. 5, and the peak-valley difference rate and cost data were shown in Table 6.

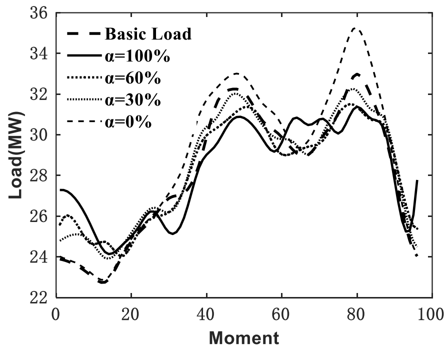

Fig.5 Load curves of different response rate

Table 6. Characteristics of overall load and costs (with different response rate)

Response ratio for V2G	Peak-valley difference rate %	Charging cost/¥	Discharge earning/¥	Incremental loss cost/¥	Total costs /¥
0% Unordered	35.14	3152	/	/	3152
30%	25.90	4276	3213	1625	2688
60%	23.67	4902	6023	3317	2196
100%	23.08	6429	10359	5508	1578

As can be seen from Figure 5 and Table 6, the total cost decreases as the response rate of EV users to TOU increases. Among them, compared with unordered charging, orderly charging with V2G mechanism can obviously improve the problem of peak load balancing. The load curve with 100% response rate shows the best effect of peak cutting and valley filling. With the increase of response rate, the curve peak-valley difference rate and the total charging cost of the user gradually decrease. However, the time characteristic of unordered charging is basically the same as that of base load. After the superposition of EV charging curve and load curve, the peak-valley difference is higher than that of base load curve, and the curve fluctuation is larger.

6 Conclusions

The main conclusions are as follows.

- Based on the commuting statistics of private EVs, an EV charging/discharging characteristic analysis model considering the relationship between traffic and electricity consumption is proposed, which is the premise and basis for the optimization of charging/ discharging strategy.
- In terms of the incentive effect of TOU on demand-side elasticity, it is proposed about an orderly charging/ discharging method that takes into account the incremental battery loss cost caused by V2G, which can more accurately reflect the additional benefits and incremental costs brought by the participation of EV storage battery discharge for peak regulation of grid.
- When EV users optimize their own charging/ discharging strategies, the increase of peak-valley price difference will directly encourage more EV users to participate in V2G arbitrage in more periods. However, when the peak-valley price difference is high to a certain extent, it may lead to a new load peak on the load curve. Therefore, power suppliers need to set the TOU price reasonably for EV to play a better role in peak-load shifting under the guidance of V2G.
- Compared with unordered charging, both orderly charging and V2G can effectively reduce the peak-valley difference of the system. With the increase of the response rate of vehicle owners participating in V2G, the effect of EV charging/discharging on peak-load shifting in load curve gradually becomes better. Therefore, power suppliers need to promote and improve the response proportion of vehicle owners to participate in V2G through technical and price measures, so that EV development can not only expand the electricity market, but also contribute to the coordinated development of the grid.

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