A V2G scheduling strategy based on the fruit fly optimization algorithm

Muyao Han*

College of International Communications, China Three Gorges University, Yichang, China

*Corresponding author e-mail: hanmuyao@mail.ctgu.edu.cn

Abstract. As electric vehicles enter people’s lives in large numbers, their behavior of disorderly charging and discharging will have a seriously negative impact on the safety and economic operation of the power system. This study proposes an electric vehicle charging and discharging load model under the constraint of joint benefits on the both power supply and demand sides. In this model, we set the minimum variance of grid load peak-to-valley values and the maximum benefit for users as the objective function, and take into account the randomness of electric vehicle starting charging time and duration as well as the grid capacity limitation. The main innovation point is that based on the fruit fly optimization algorithm, it proposes an intelligent orderly charging and discharging strategy with vehicle-to-grid (V2G). Following this, we compare several common charging models for electric vehicles with simulations, and conclude that the proposed optimization model can best reduce the target of peak-to-valley difference in grid load and also charging and discharging costs, thus demonstrating the feasibility and effectiveness of the model and strategy.

Keywords: Electric vehicle, orderly charging and discharging, fruit fly algorithm, V2G.

1. Introduction

Given the dual pressure of the energy crisis and environmental degradation, electric vehicles have received widespread attention as a green way to travel that effectively addresses greenhouse gas emissions and energy shortages. Meanwhile, as the EVs industry continues to develop, its ownership has also shown a growing trend, yet large-scale disorderly charging behavior will place a serious burden on the smooth-running capacity and carrying capacity of the power system, and to a certain extent will also affect the quality of power. Therefore, it is of great research importance to rationalize the charging and discharging of EVs reliant on vehicle-to-grid (V2G) technology [1].

Using the characteristics of EVs as both mobile loads and energy storage devices, V2G technology guides users to charge and discharge in an orderly manner, complementing distributed energy sources and reducing the degree of impact on the grid [2-3], while also being able to increase grid revenue and user charging costs [4]. Current research on modeling with the goal of maximizing the charging profit of electric vehicles in V2G mode has achieved substantial success by many scholars internationally. In [5], Vagropoulos et al. introduce an intelligent control method based on time-of-use tariffs to control the charging periods of EVs by comparing the burden of disorderly charging on the grid. Furthermore,
Zhang H et al. establish a real-time tariff trading and charging pile intelligent control model, with its ability to improve power quality while achieving optimal grid trading profits and ensuring supply-side reliability [6]. In addition, considering the vehicle battery and the characteristics of the environment in which it is located, Xie D et al. build a multi-objective ordered charging control system as per different user requirements [7]. Depending on the orderly charging and discharging management, the [8] mentioned strategy for large-scale decentralized charging behavior with autonomous decision making by charging piles, which can manage to guide electric vehicles to play their "energy storage" even in offline state. And with the operating hours of electric buses, reference [9] is mainly focused on a multi-time-scale optimal scheduling strategy to integrate into the grid to achieve "peak and valley removal", but this strategy is highly dependent on bus operating hours and operating modes. To solve the problem of grid dispatching, Su Shu et al. improve fast-charging stations into predictable ones, guiding users to change their charging behavior, but without considering factors such as alleviating traffic conditions and reducing users' charging waiting time.

At present, relatively few scholars have used intelligent optimization algorithms to realize grid interactive dispatching strategies on the premise that both the supply side and the demand side benefit from each other. Considering the above, this paper establishes a two-layer optimization model for charging and discharging EVs: the grid company minimizes the variance of the total load level by collecting the dispatching plan of each owner in the lower layer and the EV owners, who are motivated to change the charging and discharging periods of their EVs, should conform to the schedule set by the grid company and respond to the expected range of total load variance predicted. Meanwhile, considering the common interests of grid side and customer side, the model develops a time-sharing charging and discharging tariff scheduling scheme that benefits both sides. Finally the model is chosen to adopt a newer intelligent optimization algorithm, fruit fly optimization algorithm (FOA) [11], to optimize the electric vehicle battery discharge strategy, and the feasibility and effectiveness of the model is verified by simulation.

2. V2G charging and discharging strategy

2.1. Electric vehicle travel time distribution model

Reference [12] conducted data statistics based on the distribution pattern of EVs travel time in real-life residential areas, through the normalization of the statistical graph data, and fitted that the travel time approximately obeys a normal distribution.

The travel and return trip probability model is shown in equation

\[ f_{\mu_1,\sigma_1}(x) = \frac{1}{\sqrt{2\pi\sigma_1}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \]  \hspace{1cm} (1) \]

The return distribution probability density function is:

\[ f_{\mu_2,\sigma_2}(x) = \frac{1}{\sqrt{2\pi\sigma_2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}} \]  \hspace{1cm} (2) \]

In the equation, \( x \) is the user's travel time and return time, \( \mu_1 \) and \( \mu_2 \) is the expectation, \( \sigma_1 \) and \( \sigma_2 \) are the standard deviation; Among the travel distribution, \( \mu_1=8.0, \sigma_1=1.33 \), the return distribution parameter is \( \mu_2=18.5, \sigma_2=1.99 \), whether or not to go out is then randomly generated and the total probability of residents traveling is assumed to be 0.8.

The probability density function of the daily mileage of EV is:

\[ f_s(x) = \frac{1}{x\sigma_s\sqrt{2\pi}} e^{-\frac{(\ln x-\mu_s)^2}{2\sigma_s^2}} \]  \hspace{1cm} (3) \]
Where, \( x \) is the EVs daily mileage. \( \mu_s \) is the expectation, \( \sigma_s \) is the standard deviation; of which \( \mu_s = 3.2 \), \( \sigma_s = 0.88 \).

2.2. Electric vehicle discharge model

For the study of V2G, the optimal charging power time distribution derived from the load forecast information and analysis in the literature [8] is used to calculate the discharge margin of the grid in each time period for providing a data basis for the grid company to make decisions on the behavior of EVs, while guiding users to orderly charging and discharging.

The charging margin refers to the highest charging load capacity that the grid can allow EVs to bear in a certain period of time, expressed as the optimized charging load; the discharge margin refers to the highest load-consuming capacity of EVs discharging to the grid in a certain period of time, expressed as the difference in power between the peak load discharge offsetting forecast demand and the optimized load. As a result, the discharge margin model is shown in the equation

\[
P_{\text{dem}}(i) = \begin{cases} \int_{t_i}^{t_{i+1}} (P^*(t) - P(t))dt, & P^*(i) \geq P(i) \\ 0, & P^*(i) < P(i) \end{cases}
\]

Where, \( P_{\text{dem}}(i) \) indicates the discharge margin for time period \( i \), \( P(t) \) indicates the charging load at moment \( t \) after optimization, \( P^*(i) \) is the forecasted load value of the grid in time period \( i \). When the predicted charging load in time period \( i \) is greater than the optimized charging load, \( P_{\text{dem}}(i) \) is equal to the integral of the difference between the two in time periods \( t_i \) to \( t_{i+1} \), otherwise it is equal to 0.

3. Two-layer optimization-based optimal dispatching model for EVs and grids

V2G revenue cost serves as an important means for users to participate in decision-making grid dispatch, and the reasonable development of time-of-use tariffs can change user charging and discharging behavior to achieve auxiliary smoothing of grid load fluctuations, while reducing battery losses as well as power consumption behavior [14]. Based on the time-sharing tariff, the demand side is able to allocate the grid connection time and charging time for the EVs, both in terms of time cost and revenue cost, which is more efficient than the traditional unstructured non-time sharing tariff. However, in reality, not all users are able to actively and positively respond to the charging plan developed by the grid company owing to the influence of different environments and different travel options, hence it is also necessary to develop a set of incentives for users to cooperate with V2G to motivate owners to be able to join the distribution grid dispatching process under the condition of satisfying their own trips. Therefore, in this paper, we choose to model the minimum grid load variance and the minimum V2G cost, respectively.

3.1. Power grid and user interaction dispatch model

3.1.1. Upper layer optimization model. The upper layer optimization model consists of an upper layer objective function that contains a range of variance for the total load level of the grid system and 2 incentives developed by the grid company for the actual dispatch results of each agent in the lower layer. The grid-side load is composed of two parts: the base load available in the grid and the EV charging and discharging load, so it can be expressed as

\[
F_c = \min \frac{1}{T} \sum [(P(t+1) + EV_{\text{load},t+1}) - (P(t) + EV_{\text{load},t})]^2
\]

Where, \( P(t+1) \) and \( P(t) \) denote the base load in the grid at times \( t+1 \) and \( t \), respectively, \( EV_{\text{load},t+1} \) and \( EV_{\text{load},t} \) denote the load of EVs in time period \( t \), respectively.

Aiming to realize the interaction between the grid and electric vehicles as well as to promote users to actively change their own charging and discharging behavior, incentives for users to participate in
smooth load curve behavior are added on the basis of load variance, and the incentive cost $R$ can be expressed as

$$ R = \varphi F_c T $$

(6)

Where, $\varphi$ denotes the reward factor for users who meet the grid company's load variance target, and its value depends on the grid's target variance for the day. $T$ denotes the total number of time periods during which users participate in orderly charging and discharging behavior and meet the grid requirements.

Constraint Conditions

When electric vehicles are integrated into the grid for power transmission in a disorderly manner, the capacity of the distribution grid is affected to a certain extent owing to the increase in quantity and the difference in battery capacity, which might form a new load peak-to-valley difference. Consequently, the grid company sets the value of the allowable range of load variance at the level of user behavior rewards, which enables the electric vehicle behavior to help the distribution network to a great extent to meet the grid company requirements. The mathematical expression for the given user reward constraint is

$$
\begin{align*}
R, & \quad F_c \leq F_{c,s} \\
0, & \quad F_c > F_{c,s}
\end{align*}
$$

(7)

Where, $F_{c,s}$ indicates the maximum value of the allowed range of expected load variance based on the comprehensive analysis of the recent power consumption by the grid company. Only when the variance of the grid load after adding the scheduling strategy is less than the expected value of the grid, the customer can get the corresponding reward. If the electric vehicle does not reach the expected range due to factors such as charging and discharging duration or battery capacity, the user will not be rewarded. The simulation results show that the load variance as the target for the distribution network for peak and valley reduction can indeed smooth the load power to a certain extent, and accomplish the requirements for vehicle cluster load transfer in a small area, so that the user charging and discharging costs are reduced on the basis of disorderly charging, however, it still cannot solve the load bearing pressure on the grid side during the peak load hours of the peak electricity consumption period, and the load fluctuation of the distribution system still exists.

3.1.2. Lower layer optimization model.

V2G strategy is not only related to user-side cost optimization, but also usually involves grid losses, load balancing and other practical problems. It is impossible to achieve the expected efficient operation mode of the grid simply by controlling the variance coefficient for peak-shaving and valley-filling, so considering the relevant factors affecting load fluctuation on both grid side and user side can improve the stable operation of the grid, thus developing user charging and discharging cost optimization as the lower layer optimization model.

Given that the user side has a more diversified choice of charging methods due to different travel reasons and travel frequency, grid companies can develop multiple types of charging modes and charging pricing that meet user needs. Meanwhile, electric vehicles have dual characteristics of charging and discharging as mobile energy storage devices, and they can also be used as random distributed power sources to deliver electricity to the distribution network, allowing users to obtain discharge gains while helping the distribution network system to operate stably. With the constraints and incentive mechanism of peak and valley reduction coefficients, the discharge gains of users $B_u$ can be expressed as

$$ B_u = w_{u,s}(\vartheta) p_{E3} \eta_u(t) + R $$

(8)

Where, $p_{E3}$ denotes the amount of electricity discharged by an electric vehicle at a charging post in a residential neighborhood or parking lot, the value of which depends on the value of the electric power that the customer expects the electric vehicle to transmit to the distribution system. $w_{u,s}(\vartheta)$ is the user-side discharge decision factor, the value of which is determined in relation to whether the user chooses...
to have the electric vehicle charged or not. $\eta_{uc}(t)$ denotes the time-of-day discharge tariff (yuan/kwh) developed by the grid company based on system operation and revenue costs.

Combining the above influencing factors, the charging and discharging cost $C_{uc}$ of electric vehicles can be expressed as

$$C_{uc} = \omega_{ch} \sum_{i=1}^{N} B_u - \sum_{j=1}^{N} \sum_{j=1}^{J} \lambda_{k}(\theta_1) P_{EV,f}(t) (t_{end} - t_{start}) + \lambda_{k}(\theta_2) P_{EV,f} (t)(t_{end} - t_{start})$$

(9)

Where, $\omega_{ch}$ denotes the grid-side discharge decision factor, the value of which depends on the length of time the electric vehicle is connected to the grid for charging and discharging. $\lambda_1(\theta_1)$ is the fast charging decision variable, if the user chooses fast charging according to his travel situation, then $\lambda_1(\theta_1) = 1$, conversely, $\lambda_1(\theta_1) = 0$; $\lambda_2(\theta_2)$ is the slow charging decision variable, if the user decision outcome is slow charging of electric vehicles, then $\lambda_2(\theta_2) = 1$, conversely, $\lambda_2(\theta_2) = 0$, and the fast and slow charging decisions do not hold simultaneously during the conventional charging process, i.e. $\lambda_1(\theta_1)$ and $\lambda_2(\theta_2)$ cannot be 1 at the same time; $\rho_1(t)$ is the slow charging tariff (yuan/kwh), $\rho_2(t)$ is the fast charging tariff (yuan/kwh), Both of them are divided into peak, low and flat periods within a day according to the changes of the grid load, and different tariffs are formulated for the characteristics of the load curve in different periods to encourage users to choose the charging mode and charging time reasonably, which has the effect of peak and valley reduction, and

$$\rho_1(t) < \eta_{uc}(t) < \rho_2(t) ; \quad P_{EV,f}$$

denotes the total charging power in time period $t$ where the electric vehicle is located. $t_{start}$ and $t_{end}$ denotes the starting moment and the leaving moment of the electric vehicle user's access to the charging pile, respectively.

Constraint Conditions

1. User-side discharge decision factor constraint

$$w_{us}(\theta) = \begin{cases} 1, & \text{Electrical vehicles are involved in discharges} \\ 0, & \text{Electrical vehicles are not involved in discharges} \end{cases}$$

(10)

2. Electric vehicle charging behavior when fast charging and slow charging can not be carried out at the same time

$$\lambda_1(\theta_1) + \lambda_2(\theta_2) \leq 1$$

(11)

3. Grid-side discharge decision factor constraint

$$\omega_{ch} = \begin{cases} 1, & T_{ch} \geq \Delta T_{ch} \\ 0, & T_{ch} < \Delta T_{ch} \end{cases}$$

(12)

Where, $T_{ch}$ denotes the total time of continuous charging and discharging of the user to the grid. $\Delta T_{ch}$ denotes the minimum access dwell time to the grid for which grid companies specify that electric vehicles are allowed to take discharge measures. It guarantees that when leaving the grid, the SOC of the electric vehicle will still ensure normal travel for the user even if the user selects the discharge mode due to other conditions by terminating the interaction between the electric vehicle and the distribution network in advance.

4. Safety constraints on battery operation

$$SOC_{min} \leq SOC_{n,t} \leq SOC_{max}$$

(13)

Of which, $SOC_{min}$ and $SOC_{max}$ denotes the maximum and minimum values of the electric vehicle charge state, respectively.
5. Power constraints for charging and discharging of electric vehicles in adjacent time periods

\[ |EV_{load,t+1} - EV_{load,t}| \leq \Delta EV_{p_{\text{min}}} \]  

(14)

Of which, \( \Delta EV_{p_{\text{min}}} \) denotes the maximum charging power allowed in adjacent time periods under electric vehicle charging status.

6. Electric vehicle charging and discharging capacity constraints

\[
SOC_{N,t+1} = \begin{cases} 
SOC_{N,t} + \frac{\mu_{ch} P_{N,t} (t_{\text{end}} - t_{\text{start}})}{SOC_{m}}, & w_{u,t} (\theta) = 0 \\
SOC_{N,t} - \frac{\mu_{sp} P_{N,t} (t_{\text{end}} - t_{\text{start}})}{SOC_{m}}, & w_{u,t} (\theta) = 1 
\end{cases}
\]  

(15)

Where, \( SOC_{N,t} \) denotes the state of charge at the end of moment \( t \) when the electric vehicle is connected to the grid. \( \mu_{ch} \) and \( \mu_{sp} \) denotes the charging efficiency and discharging efficiency of charging piles in residential neighborhoods or parking lots, respectively. \( P_{N,t} \) denotes the charging and discharging power provided by the user's choice of grid connection mode. \( SOC_{m} \) denotes the battery capacity in the user's electric vehicle.

7. Unschedulable time constraints

\[
\begin{cases} 
w_{u,t} (\theta) = 0 \\
\lambda_{1} (\theta_1) = 0, \forall N, t < t_{\text{start}} \text{ OR } t_{\text{end}} \\
\lambda_{2} (\theta_2) = 0 
\end{cases}
\]  

(16)

Where, if the charging period \( t \) is smaller than \( t_{\text{start}} \) or \( t_{\text{end}} \), it is impossible for the grid company to schedule EVs charging and discharging behavior, which means \( w_{u,t} (\theta) \), \( \lambda_{1} (\theta_1) \) and \( \lambda_{2} (\theta_2) \) all equal to zero.

4. V2G scheduling strategy for electric vehicles based on fruit fly algorithm

4.1. Fruit fly algorithm

As the intelligent algorithms continuously improve and develop, many studies have achieved good results for the processing of multi-optimization problems, especially about the optimization problem of orderly charging and discharging of electric vehicles, most scholars at home and abroad choose to take Particle Swarm Optimization, PSO algorithm to find the optimal solution of the problem in the grid or user strategy [15-17], however, PSO suffers from the disadvantages of slow computation speed and easy to fall into local optimum, which has a great degree of influence on the accuracy of the algorithm. Newer group intelligence optimization algorithms, the fruit fly optimization algorithm principle is easy to understand, easy to implement programmatically, has fewer control parameters, and is easy to embed in specific search sessions targeted to the problem. Due to the convenience and speed of the Drosophila optimization algorithm to deal with optimization problems, it has been successfully applied to network energy efficiency optimization, logistics, planning, and scheduling problems in a relatively short time [18-20]. In recent years, the algorithm is gradually being applied to positioning in the case of electric vehicles connected to the grid [21], with good results.

4.2. Algorithm Process

According to the fruit fly optimization algorithm, the steps for optimizing the layout of EV charging stations in this paper are shown in Figure 1.
Step 1: The original parameters are set and initialized for data processing, including user electric vehicle charging and discharging information (charging and discharging power, battery capacity, charging demand, etc.) and parameters such as grid-side base load information and predicted load variance are set.

Step 2: Depending on the scope of the target area, the charging and discharging load power in different areas at different times is calculated and the charging and discharging driving cost of users is converted.

Step 3: Optimized values in each range are found by updating the calculated particles by fitness

Step 4: Determine whether the maximum number of iterations is exceeded, if not, repeat steps 2 and 3, and vice versa to find out the optimal particle positions and adaptation values with respect to different charging and discharging strategies, and end the simulation.

5. Example analysis

5.1. Parameter Setting

In this paper, the formal characteristics of domestic electric vehicles and grid base load curves from the literature [8] are used as references. For ensuring that the maximum optimization of user-side charging and discharging costs is reached, \( w_{\text{u},1}(\theta) = 1 \) and \( \omega_{1,1} = 1 \), namely, all users select the slow charging mode and agree to participate in the discharge decision and the grid connection time meets the specified length.

The grid sets tariffs in the form of time-of-day tariffs. The time-of-day tariff is divided into 3 periods: peak, usual and valley, and the grid company sets the corresponding tariff for each period. With the aim of providing a better charging experience and power quality, as well as motivating users to choose to
consume as much as possible when the price is lowest in the valley and discharge to the grid when the revenue is highest in the peak time, a time-sharing tariff has been implemented in some areas on a trial basis, with the specific development of charging and discharging price parameters set as shown in Table 1. If we suppose that the charging station provides charging service for 24 private electric vehicles per day, and analyze the general habits of residential users in using electric vehicles, we find that the distribution of users’ starting charging time and charging capacity conforms to a normal distribution \( N(18,3^2) \).

The research time starts from 1:00 and ends at 24:00 on the next day. For the sake of more intuitive and simple research results, we set the time gap as 1 hour, that is, 1 day is divided into 24 periods, 1:00-2:00 is 1 period, and so on. Based on the analytical calculation of the grid base load in the literature [8], we assume that the grid company expects the maximum value of the range of daily load curve variance to be 834, i.e. \( F_{c,s} = 834 \).

| Time period          | Slow charging tariff / (Yuan \( \cdot \) (kW \( \cdot \) h \( \cdot \) s\(^{-1} \)) \(^{-1} \)) | Regular discharge tariff / (Yuan \( \cdot \) (kW \( \cdot \) h \( \cdot \) s\(^{-1} \)) \(^{-1} \)) |
|----------------------|-------------------------------------------------|-------------------------------------------------|
| Valley time (0:00-3:00, 22:00-24:00) | 0.200                                           | 0.300                                           |
| Usual time (3:00-7:00, 15:00-17:00)    | 0.862                                           | 0.906                                           |
| Peak time (7:00-15:00, 17:00-22:00)    | 0.558                                           | 0.668                                           |

5.2. Disorderly and orderly charge/discharge simulation

Aiming at verifying the actual control effect of the model strategy on orderly charging, we first calculate the load of distribution system and the benefit of user charging and discharging in the case of disorderly charging, then compare and analyze the arithmetic results with the case of orderly charging. When charging in an unordered manner, new entrants can be charged as long as there is space available at the charging station, until the user leaves, otherwise the charging should stop if the electric vehicle battery is full. Prior to the electric vehicle being connected to the grid, the grid system itself contains comprehensive power consumption in residential areas and line network loss consumption to form a base load with large power differences at various times. However, when electric vehicles are integrated into the grid in a disorderly manner, the charging station may overload the distribution transformer during peak hours of power consumption due to the access of a large number of electric vehicles, or the user's demand may be urgent, requiring the state of charge in a short period of time, then occur the situation that the battery cannot be fully charged when leaving even if the electric vehicle has been charging. While in the case of orderly charging and discharging, no increase in the peak-to-valley difference in the base load curve after accessing electric vehicles according to the guidance of the time-sharing tariff strategy developed in advance, while the user cost is also reduced compared to disorderly charging. As a result, the time-sharing tariff strategy in the context of unordered charging remains ineffective in solving the problems of load fluctuation and minimum cost for users in the distribution network during the peak electricity consumption period, while ordered charging can provide problem solving options.

5.3. Simulation results based on the fruit fly optimization algorithm

Optimization analysis is carried out by fruit fly algorithm according to the selected parameter settings with the maximum benefit cost of user discharge as the objective function, and the calculation results under the disorderly charging mode and the orderly charging mode are calculated, in which the optimal
discharge power curve is superimposed on the conventional load and the electric vehicle charging load in the grid to obtain the daily load expectation curve and the conventional load curve under the two modes of disorderly charging and orderly charging.

5.4. Result Analysis
Table 2 is derived from the model data results and analyzes that the user cost decreases by 2.5 times in the orderly charging mode compared with the disorderly charging mode, which proves that the interaction between the user's orderly charging and discharging and grid dispatching is conducive to achieving the optimal demand-side benefit on the premise of meeting the stable operation of the grid. From Figure 2, we can see that when this strategy adopts the orderly control of electric vehicle charging and discharging, after 24 electric vehicles are integrated into the grid, the minimum load value is increased from 192 KW to 287.875 KW after optimization, and the peak-to-valley difference is reduced from 252 KW in disorder to 108.783 KW after optimization, and the load power variance in the grid is reduced from 4982 kW2 to 1085.66 kW2, with obvious effect of "peak reduction" during the peak hours of electricity consumption. It also effectively adjusts the charging behavior moment to 1:00 to 4:00, while the discharging behavior is concentrated in the two peak hours of electricity consumption from 9:00 to 13:00 and 18:00 to 20:00. Compared with the charging and discharging tariff, the higher rebate reward can be obtained by choosing to discharge to the grid in these two periods compared with other periods. With the fruit fly optimization, this scheduling scheme can indirectly assist the grid to reduce the peak-to-valley difference of the load curve and play the role of peaks and valleys reduction while achieving the goal of saving users' charging cost.

| Charging and discharging cost model | Disorderly charge | Orderly charge and discharge |
|-----------------------------------|------------------|-----------------------------|
| Charging cost (yuan)              | 4328.46          | 4096.50                     |
| Discharge earnings (yuan)         | 0                | 2379.53                     |
| Total (yuan)                      | 4328.46          | 1716.97                     |

Table 2. Charging and discharging costs of electric vehicles under different modes

| Mode | Basis load | Disorderly charge | Orderly charge and discharge |
|------|------------|-------------------|------------------------------|
| Load variance (kW^2)               | 7124.41       | 4982              | 1085.66                      |

Table 3. Load variance of distribution network system under different modes

Figure 2. Comparison among disorderly charging and optimal charging and discharging
Consequently, this calculation shows that the V2G mode dispatching strategy for home electric vehicles that sets the load variance range on the grid side and maximizes the charging and discharging costs for vehicle owners can motivate electric vehicle users to participate in grid dispatching interactions, with a mechanism to provide incentives for discharging to the grid helping to promote the goal of user response to the time-of-use tariff. Simultaneously, this example also proves that a scientific and reasonable electric vehicle dispatching strategy can provide technical support to the "peak and valley reduction" scheme of the distribution network and effectively help the grid system maintain a stable operation.

6. Conclusion
This paper mainly deals with the application of V2G strategy based on FOA for home EVs in residential communities, which sets the expected range of grid load variance affected by the grid connection of electric vehicles by analyzing the actual grid base load distribution, while considering various constraints such as decision factors of both sides, battery capacity and charging and discharging power. It is demonstrated that the strategy can promote the users to respond to the grid company's proposal by comparing the grid load power under the disorderly charging mode, thereby enabling the access of electric vehicles to achieve the goal of smoothing the electricity load curve in the distribution system, realizing the goal of grid peaks and valleys reduction, and ensuring the stability of grid system operation and power quality.

The proposed scheme is based on the behavior of clustering vehicles in a small area, while the user chooses to participate in the optimal scheme to the maximum extent to achieve the minimum charging cost. The charging behavior of electric vehicles is directly related to the load fluctuation on the distribution side, while in reality, users cannot prefer such strategies as per their own travel needs at the moment, season, weather and other factors. Consequently, it is advisable to consider the response of users' multifaceted travel factors to their charging and discharging behaviors under different scenarios in the subsequent study in conjunction with the actual situation.

References
[1] Alam M, Muttaqi K M, D Sutanto. Effective Utilization of Available PEV Battery Capacity for Mitigation of Solar PV Impact and Grid Support With Integrated V2G Functionality[J]. IEEE Transactions on Smart Grid, 2017, 7(3):1562-1571.
[2] YANG H, PAN H, Luo F, et al. Operational planning of electric vehicles for balancing wind power and load fluctuations in a microgrid[J]. IEEE Transactions on Sustainable Energy, 2017, 8(2).
[3] NIEY, CHUNG C, XU N. System state estimation considering EV penetration with unknown behavior using quasi-Newton method [J]. IEEE Transactions on Power Systems, 2016, 31(6):4605-4615.
[4] Cheng Suan, Wang Xianning, Feng Yi Brazier. Decentralized optimization of orderly charging scheduling for electric vehicle charging stations[J]. Power System Automation, 2018,42(01):39-46.
[5] Vagropoulos S I, Balaskas G A, Bakirtzis A G. An Investigation of Plug-In Electric Vehicle Charging Impact on Power Systems Scheduling and Energy Costs[J]. IEEE Transactions on Power Systems, 2017, 32(3):1902-1912.
[6] Zhang H, Hu Z, Xu Z, et al. Evaluation of Achievable Vehicle-to-Grid Capacity Using Aggregate PEV Model[J]. IEEE Transactions on Power Systems, 2017, 32(1):784-794.
[7] Xie D, Chu H, Gu C, et al. A Novel Dispatching Control Strategy for EVs Intelligent Integrated Stations, IEEE Transactions on Smart Grid, 2017,8(2):802-811.
[8] Wang Yi, Ma Xiu, Wan Yi, Hou Xingzhe, Zheng Ke, Chen Wenli. Orderly charging and discharging guidance strategy for electric vehicles based on time-sharing charging and discharging margins[J]. Power Grid Technology, 2019,43(12):4353-4361.
[9] Chen Lijuan, Qin Meng, Gu Shaoping, Qian Kejun, Xu Xiaohui. Optimal scheduling strategy for
electric buses participating in V2G taking into account battery losses[J]. Power System Automation, 2020, 44(11): 52-60.

[10] Su Shu, Lin Xiangning, Zhang Hongzhi, Zhao Hang, Li Hao, Li Zhentian. Dynamic evolution model of spatial and temporal distribution of electric vehicle charging demand[J]. Chinese Journal of Electrical Engineering, 2017, 37(16): 4618-4629+4887.

[11] Fan Y, Wang P, Heidari A A, Wang M, Zhao X, Chen H, Li C. Rationalized fruit fly optimization with sine cosine algorithm: A comprehensive analysis [J]. Expert Systems With Applications, 2020, 157.

[12] Shi Ruifeng, Liang Zihang, Ma Yuan. An orderly charging strategy for electric vehicles in residential areas based on TOPSIS method[J]. Power System Automation, 2018, 42(21): 104-110+159.

[13] Cui Jindong, Luo Wenda, Zhou Niancheng. Research on the pricing model and strategy for orderly charging and discharging of electric vehicles based on multiple perspectives[J]. Chinese Journal of Electrical Engineering, 2018, 38(15): 4438-4450+4644.

[14] Zhang H, Hu Z, Xu Z, et al. An Integrated Planning Framework for Different Types of PEV Charging Facilities in Urban Area[J]. IEEE Transactions on Smart Grid, 2017, 7(5):2273-2284.

[15] Li Xianshan, Chen Minrui, Cheng San, Chen Aobo. Optimal scheduling strategy for electric vehicle microgrid based on double incentive cooperative game[J]. High Voltage Technology, 2020, 46(07): 2286-2296.

[16] Ma Xiufan, Wang Hao, Li Ying, Wang Chao, Hong Xiao. Electric vehicle charging station planning based on variable-weight Voronoi diagram and hybrid particle swarm algorithm[J]. Journal of Electrical Engineering Technology, 2017, 32(19): 160-169.

[17] Xu Fangwei, Tan Yangyang, Yang Hongkeng, Teng Yufei, Zhang Xi, Yin Qing. Optimal layout of centralized charging stations taking into account the interests of different players[J]. High Voltage Technology, 2017, 43(04): 1256-1262.

[18] Liu Yong, Sun Jingjie, Wang Xuan. Research on multiple distribution center site selection problem based on immune fruit fly hybrid optimization algorithm[J]. World Science and Technology Research and Development, 2015, 37(1): 83-87.

[19] Bian X Y, Yan G, Lo K L, et al. Coordination of PSSs and SVC Damping Controller to Improve Probabilistic Small-Signal Stability of Power System With Wind Farm Integration[J]. IEEE Transactions on Power Systems, 2016, 31(3): 1-12.

[20] Yuan Wenbing, Chang Liang, Xu Zhubo, et al. Multi-station assembly sequence planning based on fruit fly optimization algorithm [J]. Computer Science, 2017, 44 (4): 246-251.

[21] Wan Xiaofeng, Xi Ruixia, Hu Hailin, Wan Xiaoli. Research on multi-objective optimal control of grid-connected inverters during grid imbalance based on fruit fly algorithm[J]. Power Grid Technology, 2018, 42(05):1628-1635.