Research on multi-objective optimal scheduling strategy of photovoltaic and energy storage based on dynamic programming

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Abstract. The multi-objective model of the electric vehicle and wind power in the load control is established, which stabilizes the peak and valley difference of load and electric vehicle charging and discharging cost. Considering the electric vehicle battery available capacity and charge discharge power constraints, as well as the genetic algorithm for nonlinear programming, this paper analyzes the influence of peak load difference on stabilizing the load fluctuation and improving the return of electric vehicle users. Finally, through the example analysis results show that the multi-objective model can be more optimized through the reasonable price in the electric vehicle charging and discharging and genetic algorithm for nonlinear programming and considering the peak and valley load difference, and the results curve is presented.

Keywords: electric vehicle, PV power grid connection, cooperative scheduling, multi-objective optimization, nonlinear genetic algorithm.

1. Introduction
China has reached the leading position in the global new energy vehicle market because of its strong capital and market advantages. As a prominent representative of renewable energy development, electric vehicles have replaced traditional fuel vehicles and became an important trend leading the development of the automotive industry. In the future, the mass access of electric vehicles will have a great impact on the stable operation of the power system [1-5], there are mainly voltage, grid loss and harmonic research at the level of system distribution network at present. Wang Hui uses Monte Carlo algorithm to simulate the charging and discharging power curve of electric vehicles by analyzing the influence of load, voltage and network loss in the system according to different electric vehicle penetration rates [6]. Hu Wenping uses a two-tier optimization strategy to optimize the charging and discharging plan of electric vehicles at the transmission and distribution network levels respectively [7].

With the large-scale promotion of electric vehicles, the vehicle-to-grid (V2G) technology will bring a huge change to the operation of today's power grids [8]. V2G can not only improve the efficiency of power grids, but alleviate the problem of volatility of renewable energy to a certain extent, and can also create benefits for electric vehicle users [9]. Liu Xiaofei gives four implementation methods of centralized, autonomous, microgrid-based, and battery pack replacement for V2G conducting intelligent
charging and discharging management of V2G from the perspective of the power grid and from the perspective of users respectively [10].

With the development of renewable energy, the proportion of photovoltaics in the world's energy structure continues to increase, and the impact of photovoltaic grid-connected on the power system is also increasing. In the system, photovoltaic grid connection will be accompanied by a certain phenomenon of abandonment of light, resulting in a waste of energy, so improving the ability of the power system to absorb photovoltaics has become the focus of current research.

Figure 1 shows the wiring diagram of electric vehicles and photovoltaic grid-connected. At present, some scholars have conducted research on the related issues of electric vehicle charging and discharging and renewable energy grid-connected coordinated scheduling. Lu Jianli uses multi-objective genetic algorithm to obtain the pareto solution set by constructing a multi-objective function of user electricity cost and economic dispatch cost, selects the appropriate solution can reduce the total cost [15]. Zhang Xiaohua established a stochastic collaborative optimization scheduling model to minimize the active power processing fluctuation of renewable energy, which is a single-objective optimization problem [16]. Wu Hongbin verifies that the orderly charging and discharging of electric vehicles can optimize the operating costs, environmental benefits and overall costs of the construction through four different strategies [17]. Luo Zhuowei used the integer programming method to optimize the charge and discharge load of electric vehicles by establishing a two-stage model of grid peak load and coincidence fluctuation [18]. Wang Guibin uses the cross-entropy algorithm to solve the constructed load fluctuation target model which ignoring the economic benefits of electric vehicle users and the load peak-valley difference after adjustment [19].

![Fig. 1 Electric vehicles and pv power grid connection](image)

It can be seen from the above introduction that there have been related studies on the coordinated dispatch of electric vehicles connected to the grid and photovoltaic grid-connected, but the research on the load peak-valley difference has been ignored. This paper establishes a multi-objective coordinated scheduling model to stabilize grid load fluctuations, reduce charging and discharging costs of electric vehicle users, and reduce the load peak-valley difference. It is considered more comprehensive, and optimized by a function optimization algorithm based on nonlinear programming.

2. Multi-Objective Scheduling Model

2.1. Establishment of multi-objective model

In order to optimize the coordinated scheduling of photovoltaic power generation systems and electric vehicle charging systems, this paper establishes a research to stabilize the grid load fluctuations, reduce the charging and discharging costs of electric vehicle users, and reduce the load peak-valley difference. According to the habits of electric vehicle users, the stopping probability of electric vehicles in one day is shown in Figure 2. Taking into account the strong randomness of the charging and discharging time of electric vehicles and photovoltaic output, a scheduling cycle is set as 1 day, and 1 day is divided into...
24 time periods, and the electric vehicle charge and discharge power in each time period is used as an optimization variable through the time-of-use electricity price.

\[ P_{\text{avg}} = \frac{1}{24} \sum_{t=1}^{24} (P_{\text{lt}} - P_{\text{ct}} + P_{\text{ct}} - P_{\text{ct}}) / 24 \]  

Where, \( P_{\text{wt}} \) is the total power generation value of each photovoltaic field in the regional power grid in the \( t \) period; \( P_{\text{lt}} \) is the total load demand value in the \( t \) period in the regional power grid; \( P_{\text{avg}} \) represents the average value of the load sum of the power system in each period within a day; \( P_{\text{evt}} \) is the charging and discharging power of all electric vehicles in \( t \) period.

- Construct an objective function (considering the loss cost \( C_b \) caused by the battery during charge and discharge of electric vehicles) to meet the charge and discharge needs of electric vehicle users and reduce charge and discharge costs:

\[ \min P_t = \sum_{t=1}^{24} (r_1 P_{\text{ct}} + r_2 P_{\text{ct}}) \Delta t \]  

\[ r_b = \frac{C_b}{0.8k} \]  

Where, \( r_1 \) is the charging price for the time period \( t \) when the electric vehicle is charged and discharged according to the time-of-use price; \( r_2 \) is the discharge price for the time period \( t \) when the electric vehicle is charged and discharged according to the time-of-use price; when \( P_{\text{evt}} \) is less than or equal to 0, \( r_1=0, r_2=1 \); otherwise, \( r_1=1, r_2=0 \); when \( P_{\text{evt}} \) is less than or equal to 0, it represents electric vehicle discharge, otherwise, it represents charging; \( \Delta t \) is the length of calculation time; \( C_b \) is the battery price per unit capacity of an electric car. Take a certain model of M1 as an example for an electric car. The battery capacity is 20 kW, and the battery price is 2756.8 yuan/kWh; \( k \) is the number of cycles that can be used for the full life of the battery, set to 1 200 times, \( rb = 0.143 \) 5 yuan/kWh.

- Adjusted load peak-valley target model:

\[ P'_{\text{lt}} = P_{\text{lt}} - P_{\text{ct}} + P_{\text{ct}} \]  

\[ \min P_t = \max(P'_{\text{lt}}) - \min(P'_{\text{lt}}) \]  

Where, \( P'_{\text{lt}} \) is the adjusted load curve of the original load curve; \( PL \) is the peak-to-valley difference of the adjusted load curve.
2.2. Restrictions

The constraints of constructing the above objective function are mainly manifested in three aspects: charge and discharge power constraints, battery storage energy constraints and available time.

- **Constraints of electric vehicle charging and discharging power**

\[
P_{\text{evch}} \leq P_{\text{ev}} \leq P_{\text{evdh}} \tag{7}
\]

\[
P_{\text{evch}} = -N_2 P_{\text{evmax}} \tag{8}
\]

\[
P_{\text{evdh}} = N_2 P_{\text{evmax}} \tag{9}
\]

\[
N_2 = N_\text{ev} - N_1 \tag{10}
\]

Where, \(P_{\text{ev}}\) is the charge and discharge power of all electric vehicles that can be dispatched in the \(t\) period; \(P_{\text{evmt}}\) is the minimum charge and discharge power of all electric vehicles that can be dispatched in the \(t\) period; \(P_{\text{evMt}}\) is the maximum charge and discharge power of all electric vehicles that can be dispatched in the \(t\) segment; \(N_\text{ev}\) is the total number of all electric vehicles that can be dispatched; \(N_1\) is the total number of all electric vehicles running in the \(t\) period; \(N_2\) is the total number of all electric vehicles stopped in the \(t\) period.

- **Constraints of battery storage capacity**

Extremum constraints on the remaining power of electric vehicle battery:

\[
S_{\text{min}} \leq S_{\text{t+1}} \leq S_{\text{max}} \tag{11}
\]

\[
S_{\text{max}} = a_1 N_\text{ev} S_{\text{evmax}} \tag{12}
\]

\[
S_{\text{min}} = a_2 N_\text{ev} S_{\text{evmax}} \tag{13}
\]

Where, \(S_{\text{min}}\) and \(S_{\text{max}}\) are the minimum and maximum values of the remaining power of the battery, respectively; \(S_{\text{evmax}}\) is the maximum value of the average capacity of each electric vehicle, and \(a_1\) and \(a_2\) are at least and at most the energy that the electric vehicle can save.

\[
S_{\text{t+1}} = S_t + g P_{\text{evmax}} \Delta t - S_{\text{t}} \tag{14}
\]

Where, \(S_{\text{t+1}}\) represents the remaining power of the electric vehicle in the \(t\)-th period; \(S_t\) is the remaining battery power of the electric vehicle in the \(t\)-th period; \(S_{\text{t}}\) represents the total power consumption of all electric vehicles in the \(t\) period; \(g\) is the charging and discharging efficiency of the electric vehicles in the \(t\) period.

\[
S_{\text{t+1}} = S_t N_\text{ev} \tag{15}
\]

\[
N_2 = C_2 N_\text{ev} \tag{16}
\]

\[
S_{\text{t+1}} = S_{\text{tav}} V_{\text{ev}} \Delta t \tag{17}
\]

Where, \(S_{\text{tav}}\) represents the average power consumption of electric vehicles in a period of time; \(C_2\) represents the probability of stopping the electric vehicle in time period \(t\); \(S_{\text{kvm}}\) represents the average power consumption required for electric vehicles to drive; \(V_{\text{ev}}\) represents the average speed of electric vehicles usually driving.

The overall energy demand of electric vehicles:

\[
\sum_{i=1}^{24} P_{\text{evmax}} \Delta t = E_{\text{evn}} \tag{18}
\]

Where, \(E_{\text{evn}}\) is expressed as the total amount of electric energy required by electric vehicles in these 24 periods.

- **This paper sets the available time to 24 hours.**

3. Methods of Model Solving

3.1. Genetic algorithm for nonlinear programming

The genetic algorithm uses selection, crossover, and mutation to gradually iterate the randomly generated initial feasible solutions to generate new feasible solutions, and has a strong overall ability to search for the best feasible solutions. However, its ability to search for feasible solutions locally is relatively weak, so it can generally only get the sub-optimal feasible solution of the problem, not the
optimal feasible solution. The algorithm used in this article is to add a nonlinear programming algorithm to the genetic algorithm. On the one hand, the genetic algorithm is used to search for feasible solutions globally, and then on the basis of the global feasible solutions obtained, combined with nonlinear programming algorithms to search for feasible solutions locally to obtain the global optimal feasible solution for the problem.

The nonlinear programming problem is solved by using the fmincon function to search for the minimum value of the nonlinear multi-objective model under constraints. The following are the constraints of the function fmincon:

\[
C(x) \leq 0; \\
cep(x) = 0; \\
A \cdot x \leq b; \\
Aeq \cdot x = beq; \\
b \leq x \leq ub
\]  

(19)

Where, x,b,beq,1b and ub are vectors; A and Aeq are matrices; C(x) and cep(x) return vector functions as non-linear functions.

3.2. Algorithm flow

The algorithm flow chart is shown in Figure 3:

![Flow chart of nonlinear genetic algorithm](image)

Fig. 3 Flow chart of nonlinear genetic algorithm
The target model established in this paper is a multi-objective optimization model. In order to better realize the coordinated scheduling problem of electric vehicles and photovoltaics under V2G, the linear weighted sum method is introduced to transform the multi-objective model into a single-objective model for simulation. The single-objective model is as follows:

$$\min P = \alpha P_a / P_{\text{max}} + \beta P_b / P_{\text{max}} + \gamma P_c / P_{\text{max}}$$  \hspace{1cm} (20)$$

Where, \(a+b+c=1\).

4. Analysis of Case

Take the electricity load situation and photovoltaic field power generation situation in a certain area as an example, Figure 4 shows the electricity load demand and the output power curve of the photovoltaic field in this area within one day, and Table 1 shows the charging and discharging electricity price based on the actual electricity consumption in a certain place. The number of electric vehicles that can be dispatched is 6,000. The electric vehicles contain 50% of the electricity at the initial moment, the charge and discharge power are both 3.6 kW, the charge and discharge efficiency are both 0.9, and the battery capacity is 21.6 kWh. The average driving speed is 50 km/h, \(a_1=0.2, a_2=0.9\);

\(a=0.4, b=0.3, c=0.4\), and the average driving power consumption is 0.139 kWh/km; The population size is 200, and the number of iterations in the nonlinear genetic algorithm is 500. (The benchmark value is 100 MW)

Input raw data for simulation calculation, and the results are shown in Table 2. From the perspective of whether to consider the load peak-valley difference, it can be clearly seen that considering the load peak-valley difference can effectively smooth load fluctuations and increase the income of electric vehicle users.

![Figure 4: A demand for electricity load and wind power output curve](image)

**Table 1.** Sub period charging and discharging price setting

| Time period   | nature | Charging price (yuan/kWh) | Discharging price (yuan/kWh) |
|---------------|--------|--------------------------|-----------------------------|
| 23:00-07:00   | Trough | 0.335                    | 0.168                       |
| 07:00-10:00   | Level  | 0.718                    | 0.468                       |
| 10:00-15:00   | Peak   | 1.253                    | 1.007                       |
| 15:00-18:00   | Level  | 0.718                    | 0.468                       |
| 18:00-21:00   | Peak   | 1.253                    | 1.007                       |
| 21:00-23:00   | Level  | 0.718                    | 0.468                       |

Figure 5 shows the convergence process of the single objective function \(P\) using the nonlinear genetic algorithm. It can be seen that it is stable at about 450 iterations. Table 3 shows the charging and discharging power of the electric vehicle when the objective function reaches the optimal value obtained by solving the nonlinear genetic algorithm under the condition of the load peak-valley difference.
Table 2. Objective function values under different conditions

| Condition                          | Single objective optimization $P_l$/ MW² | Single objective optimization $PC$/ 10000 yuan | Single objective optimization $P_l$/ M W |
|-----------------------------------|------------------------------------------|-----------------------------------------------|------------------------------------------|
| Without the peak-valley difference | 5 472.8                                  | 63.49                                         | --                                       |
| Without the peak-valley difference | 5 153.2                                  | 75.27                                         | 113.46                                   |

Fig. 5 Convergence curve of nonlinear genetic algorithm

Table 3. Electric vehicle charging and discharging power with the optimal objective function value

| Time/h | Load fluctuation $P_l$ | Charge and discharge fees $PC$/ | Load peak-valley difference $P_l$/ | Multi-objective function optimization $P$ |
|--------|------------------------|-------------------------------|-----------------------------------|------------------------------------------|
| 1      | -2.012 9               | -0.928 0                      | -2.134 7                         | 1.999 1                                  |
| 2      | -1.675 7               | 0.552 7                       | -1.160 4                         | 1.960 1                                  |
| 3      | -1.609 6               | 0.151 7                       | 0.781 8                          | 1.753 6                                  |
| 4      | -1.903 6               | 1.303 6                       | -1.098 7                         | 1.706 1                                  |
| 5      | 0.177 3                | -0.739 0                      | -1.299 4                         | 0.068 0                                  |
| 6      | -0.762 2               | 0.761 2                       | -1.957 5                         | 1.646 1                                  |
| 7      | -1.688 7               | 1.195 4                       | 0.434 7                          | 0.833 4                                  |
| 8      | 0.833 7                | 1.181 8                       | 0.105 9                          | -1.443 8                                 |
| 9      | 1.162 5                | -0.690 5                      | 0.415 2                          | -1.594 0                                 |
| 10     | 1.533 9                | 0.285 1                       | 1.531 9                          | -0.889 4                                 |
| 11     | 1.687 5                | -1.283 4                      | -0.860 0                         | -1.701 9                                 |
| 12     | 1.650 8                | -0.715 4                      | 1.560 7                          | -1.160 8                                 |
| 13     | 1.972 4                | 0.999 2                       | 1.943 4                          | -1.759 6                                 |
| 14     | 0.504 7                | -0.481 0                      | 1.210 7                          | -1.264 9                                 |
| 15     | 1.232 6                | -0.389 6                      | 0.792 3                          | 0.390 9                                  |
| 16     | -1.576 0               | -0.057 1                      | 0.184 0                          | 0.766 7                                  |
| 17     | 0.613 4                | -0.167 2                      | 1.183 5                          | 1.135 5                                  |
| 18     | 0.266 8                | -1.616 1                      | 0.194 8                          | -0.648 3                                 |
| 19     | 1.440 7                | -1.661 2                      | 1.880 9                          | -0.530 5                                 |
| 20     | 1.057 0                | 0.202 6                       | 1.883 1                          | -1.793 6                                 |
| 21     | 1.812 5                | 0.225 7                       | 1.110 6                          | -1.327 7                                 |
| 22     | 1.094 6                | -1.560 4                      | 0.641 7                          | -0.776 2                                 |
| 23     | -1.685 0               | 0.548 9                       | 1.273 6                          | 1.354 5                                  |
| 24     | 1.209 6                | -1.478 0                      | -0.938 4                         | 1.619 9                                  |
Under the condition of considering the load peak-valley difference, the single objective function $P$ is optimized according to the nonlinear genetic algorithm to obtain the optimal electric vehicle charging and discharging power $P_{evt}$, and then the simulation curve diagram of the optimal value of the load fluctuation and the cost of electric vehicle users in each period are obtained, which are shown in figure 6 and figure 7.

![Load fluctuation curve of optimal charging and discharging power](image1)

**Fig. 6** Load fluctuation curve of optimal charging and discharging power

![Charging and discharging curve of electric vehicle under optimal charge discharge power](image2)

**Fig. 7** Charging and discharging curve of electric vehicle under optimal charge discharge power

5. Conclusion

This paper analyzes that the load fluctuation can be better stabilized and the profit of electric vehicle users can be improved when the load peak-valley difference is considered based on whether the load peak-valley difference is considered. And through calculation examples, it is proved that the multi-objective model can be more optimized by using nonlinear programming genetic algorithm and considering the load peak-valley difference under the reasonable arrangement of the time-of-use electricity price for the charging and discharging of electric vehicles.

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