Optimal Configuration of Energy Storage System Capacity in PV-integrated EV Charging Station Based on NSGA-III

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Abstract. In order to improve the revenue of PV-integrated EV charging station and reduce the peak-to-valley load difference, the capacity of the energy storage system of PV-integrated EV charging station is optimally configured considering the interests of both the charging station operator and the distribution grid. Firstly, for the uncertainty of charging load, the day-ahead load charging demand is calculated using Monte Carlo method with random sampling. Then, considering the economic indicators such as initial investment cost, operation and maintenance cost, interaction cost with the grid and technical indicators on the grid side, the optimal configuration model of energy storage capacity is established with the objectives of maximizing the revenue of charging stations and minimizing the peak-to-valley difference rate, and the NSGA-III algorithm is used to solve the model. Finally, the effectiveness of the proposed multi-objective optimization model is verified, three schemes with peak-to-valley difference rates of 30%, 45%, and 60% were selected to complete the optimal configuration of energy storage capacity, the economy and reliability of the system are improved on the basis of meeting the load demand, and the overall performance of the charging station is optimized.

1. Introduction

The rapid popularity of electric vehicles (EVs) has effectively relieved environmental pressure in cities, but at the same time, the fluctuating charging power generated by the large-scale EV fast charging process will have an impact on the distribution grid. The traditional electric vehicle PV charging station is equipped with energy storage system (ESS), which not only can effectively alleviate the adverse impact of charging load on the distribution network [1], but also can improve the utilization rate of PV energy and adjust the charging and discharging strategy according to the time-price to realize price arbitrage and enhance the economic benefits of the charging station. Therefore, how to maximize the economic and reliable configuration of the energy storage system is one of the key issues that need to be addressed by the "storage and charging" industry [2-3].

Some studies have been conducted on the optimal configuration of energy storage capacity for PV-integrated EV charging stations, which can be divided into the following four types according to the configuration methods: 1) energy storage capacity configuration considering indicators such as system economy and PV utilization [4-7]; 2) energy storage capacity configuration based on load demand
response [8-10]; 3) electric vehicles as auxiliary energy storage, while joint energy storage devices for energy storage capacity configuration [11]; 4) energy storage capacity configuration based on two-level planning and load multi-stage optimization [12-13].

In the references [4-7], the economics of the whole life cycle of the energy storage system and the utilization of PV power are used as the optimization objectives, which are solved by a multi-objective evolutionary algorithm, and the optimal configuration scheme of the energy storage system is obtained by comparative analysis. In the references [8-10], a load demand-side response model is constructed, and the load-side response is used as an upper-level constraint for energy storage configuration, which further improves the economics of energy storage system configuration, but does not fully consider the peak-to-valley difference of the network-side load. References [11] treats electric vehicles as distributed energy storage units and reduces the need for battery storage unit capacity in combination with user subsidy schemes. In the references [12-13], by analyzing the support role of the energy storage system for the active distribution network, a two-layer optimization model of the energy storage system is established, where the upper layer is used to construct the energy storage capacity model and the lower layer is used to solve the energy storage capacity model, and then the optimal solution of the energy storage system configuration is obtained.

In view of this, the paper analyzes the charging behavior of electric vehicle users based on the structure of PV-integrated EV charging station; then, considering the whole life cycle investment cost, operation and maintenance cost, charging service revenue and technical indexes of grid operation of the energy storage system, the optimal configuration model of energy storage capacity is established with the maximum revenue and minimum peak-to-valley difference rate of the charging station as the optimization objectives, and the NSGA-III algorithm is used to solve the above model. Finally, simulation analysis is conducted in MATLAB to verify the rationality and validity of the proposed model by comparing the effects of different energy storage capacity configurations on the comprehensive performance of the system.

2. The structure and load characteristics of PV-integrated EV charging station

2.1. System Structure

In this paper, the PV-integrated EV charging station only purchases electricity from the public grid, and does not consider the backward transmission of energy. The PV-integrated EV charging station is mainly composed of PV cell array, battery storage system, DC/DC converter module, AC/DC converter module, AC distribution network, central controller and other units, as shown in Figure 1.
2.2. Electric vehicle charging load characteristics analysis

The service targets of the charging station in the paper are electric private cars and electric cabs, where the main factors affecting the charging load are the scale of electric vehicles, starting charging time, daily driving distance and other factors. According to the experimental statistics of the National Household Travel Survey (NHTS), the starting charging time of electric private cars obeys a normal distribution of \( N(17.6,3.4) \), as shown in Equation (1).

\[
f_s(t) = \begin{cases} 
\frac{1}{\sigma_s \sqrt{2\pi}} \exp\left[\frac{(t - \mu_s)^2}{2\sigma_s^2}\right] & \mu_s - 12 \leq t \leq 24 \\
\frac{1}{\sigma_s \sqrt{2\pi}} \exp\left[\frac{(t + 24 - \mu_s)^2}{2\sigma_s^2}\right] & 0 \leq t \leq \mu_s - 12
\end{cases}
\]

Equation (1)

Where, \( \sigma_s \) and \( \mu_s \) are the expected value and standard deviation of the starting charging time of electric private cars, respectively; \( t \) is the starting charging time of electric private cars. Also assume the starting charging time of electric cab obeys uniform distribution, that is,

\[
f_s(t) = \text{randperm}(24,1)
\]

Equation (2)

Where, \( \text{randperm}(24,1) \) denotes a random integer generated in the interval \([1,24]\); \( t \) is the starting charging time of the electric cab.

According to the analysis of the national travel survey results, the daily distance traveled by electric private cars and electric cabs obeyed the log-normal distribution of \( \text{Log-N}(45,0.88) \) and the normal distribution of \( N(155.02,41.53) \), respectively, with the probability density function shown in Equation (3)-(4).

\[
f_D(s_1) = \frac{1}{s_1 \sigma_{D_1} \sqrt{2\pi}} \exp\left[\frac{\ln(s_1 - \mu_{D_1})}{2\sigma_{D_1}^2}\right]
\]

Equation (3)

\[
f_D(s_2) = \frac{1}{\sigma_{D_2} \sqrt{2\pi}} \exp\left[\frac{(s_2 - \mu_{D_2})^2}{2\sigma_{D_2}^2}\right]
\]

Equation (4)

Where, \( \mu_{D_1} \) and \( \sigma_{D_1} \), \( \mu_{D_2} \) and \( \sigma_{D_2} \) are the expected daily driving distance and standard deviation of electric private cars and electric cabs, respectively; \( s_1 \) and \( s_2 \) are the daily driving distances of electric private cars and electric cabs, respectively.

According to the above probability density function of electric vehicle travel law, the starting charging time and daily driving distance of various types of electric vehicles are randomly sampled by Monte Carlo algorithm, and the number of charging electric vehicles and the initial charge state of batteries in charging stations at different time periods can be analyzed, and the daily load demand of charging stations can be further calculated.

3. Energy storage system capacity optimization allocation model

In PV-integrated EV charging station, the PV power generation should be given priority to meet the EV charging demand. Therefore, the combination of PV power and load charging power is used as equivalent power in the paper, and the energy storage system performs power optimization for the equivalent load according to the time-sharing tariff. In order to ensure the safe and economic operation of charging stations, the economic index of daily net income of charging stations and the technical index of peak-to-valley difference rate are considered to optimize the allocation of energy storage capacity.

3.1. Objective function

3.1.1. Daily net income from charging stations

\[
F_1 = I - \left( C_{\text{investment}} + C_{\text{maintenance}} + C_{\text{op}} \right)
\]

Equation (5)
Where, \( F_1 \) is the revenue of charging station; \( I \) is the daily charging cost obtained from users by charging station; \( C_{\text{investment}} \) is the daily investment cost of energy storage system; \( C_{\text{maintenance}} \) is the daily operation and maintenance cost of energy storage system; \( C_{\text{op}} \) is the daily cost of electricity purchased from the grid by charging station.

Where, the expressions for calculating the daily charging cost and the daily investment cost of the energy storage system obtained by the charging station from the user are shown in Equations (6)-(7).

\[
I = \sum_{t=1}^{24} c_{E,V} P_{EV,t} \Delta t
\]  

Where, \( c_{E,V} \) is the charging service price of charging station in time period \( t \); \( P_{EV,t} \) is the charging power of load in time period \( t \); the operating cycle is considered as one day in the text, and the unit time period is 1h, \( \Delta t = 1 \).

\[
\begin{align*}
C_{\text{investment}} &= K_{\text{bess,d}} (C_{\text{bess}} + C_{\text{inverter}}) \\
K_{\text{bess,d}} &= \frac{d(1+d)^{\gamma_{\text{bess}}}}{365 \times (1+(1+d)^{\gamma_{\text{bess}}}-1)} \\
C_{\text{bess}} &= K_{\text{bess,E}} E_{\text{bess,N}} + K_{\text{bess,P}} P_{\text{bess,N}} \\
C_{\text{inverter}} &= K_{\text{inv}} P_{\text{bess,N}}
\end{align*}
\]  

Where, \( K_{\text{bess,d}} \) is the daily equivalent coefficient; \( C_{\text{bess}} \) is the capacity acquisition cost of energy storage system; \( C_{\text{inverter}} \) is the converter acquisition cost; \( d \) is the discount rate; \( \gamma_{\text{bess}} \) is the investment life of energy storage system; \( K_{\text{bess,E}} \) and \( K_{\text{bess,P}} \) are the unit electricity investment cost and unit power investment cost of energy storage system, respectively; \( E_{\text{bess,N}} \) and \( P_{\text{bess,N}} \) are the rated capacity and rated power of the energy storage system; \( K_{\text{inv}} \) is the converter cost factor.

The daily operation and maintenance cost of the energy storage system can be calculated from Equation (8).

\[
C_{\text{maintenance}} = K_{\text{bess,d}} K_{\text{bess,m}} P_{\text{bess,N}}
\]  

The expression for calculating the daily power purchase cost from the charging station to the grid can be expressed as:

\[
C_{\text{op}} = \sum_{t=1}^{24} P_{g,t} C_{g,t} \Delta t
\]  

Where: \( P_{g,t} \) is the power purchased from the grid at time \( t \); \( C_{g,t} \) is the price of electricity sold from the grid at time \( t \).

3.1.2. Peak-to-valley differential rate. The peak-to-valley difference ratio can be used to express the magnitude of the energy storage system's ability to participate in peak-shaving and valley-filling, which can be determined by the ratio of the peak-to-valley power difference to the peak power of the equivalent load on the grid side, as shown in Equation (10).

\[
R = \frac{(P_{\text{load,up}} - P_{\text{load,down}})}{P_{\text{load,up}}} \times 100\%
\]  

Where, \( R \) is the peak-to-valley difference rate; \( P_{\text{load,up}} \) and \( P_{\text{load,down}} \) are the peak and valley values of the equivalent load power after optimization of the energy storage system, respectively.

3.2. Constraints

3.2.1. System power balance constraint. Electric vehicle charging power, photovoltaic power, energy storage system power and grid-side power supply power should achieve power balance as follows.

\[
P_{EV,t} = P_{PV,t} + P_{g,t} - P_{\text{bess,t}}
\]  

Where, \( P_{PV,t} \) is the photovoltaic power generation; \( P_{\text{bess,t}} \) is the energy storage system power, where the negative value expressing discharging and the positive value expressing charging.
3.2.2. Energy storage system charge state constraint.

\[
S(t) = \frac{E(t)}{E_{\text{bess,N}}} \times 100\
S_{\text{min}} \leq S(t) \leq S_{\text{max}}
\]

(12)

Where, \(S(t)\) is the energy storage system charge state value at time \(t\); \(E(t)\) is the total power of the energy storage system at time \(t\); \(S_{\text{min}}\) and \(S_{\text{max}}\) are the upper and lower limits of the energy storage system charge state, respectively.

3.2.3. Grid power supply power constraint. The upper limit of the grid power supply is constrained by the rated capacity of the transformer and AC/DC converter of the optical storage charging station, as follows.

\[
0 \leq P_{g,t} \leq P_{g,\text{max}}
\]

(13)

\[
P_{g,t} \leq \min(P_{\text{TR}}, P_{\text{AD}})
\]

(14)

Where, \(P_{g,\text{max}}\) is the maximum purchased power from the charging station to the grid; \(P_{\text{TR}}\) and \(P_{\text{AD}}\) are the rated capacities of the charging station transformer and AC/DC converter, respectively.

3.2.4. EV charging power constraint.

\[
P_{\text{EV},t} \leq nP_{\text{ch,p}}
\]

(15)

Where, \(n\) is the number of charging posts in the charging station; \(P_{\text{ch,p}}\) is the rated power of a single charging post.

4. Solution method of energy storage capacity optimization configuration model based on NSGA-III

The problem of optimal capacity configuration of energy storage system in PV-integrated EV charging station has multi-objective, non-linear and multi-constraint characteristics. The solution model can be expressed as follows.

\[
f_{\text{total}} = \{\text{max } F_1, \text{min } R\}
\]

(16)

Where, \(f_{\text{total}}\) is the overall optimization objective of the energy storage system.

From the overall economy and reliability of the charging station, it is not possible to set appropriate weights for each objective function to convert it into a single objective function. At the same time, since the conventional optimization algorithm is too idealistic in its search results and cannot obtain the global optimal solution, the multi-objective evolutionary algorithm (NSGA-III) based on reference point constraints is used in the paper to solve this problem.

The NSGA-III algorithm was proposed in 2014 by scholar Kalyanmoy Det. The algorithm itself continues the overall framework idea of NSGA-II, which uses a fast non-dominated ranking mechanism to rank the fitness values of each individual after finding the Pareto optimal solution set. In response to the problem that the NSGA-II crowdedness distance method has poor convergence and diversity performance in balancing the algorithm and is difficult to solve for high-dimensional objectives, the NSGA-III algorithm introduces a reference point mechanism to retain those individuals that are non-dominated and close to the reference point, which better improves the convergence of the algorithm and maintains the diversity of the population. The solution process of the multi-objective optimization model based on NSGA-III is shown in Figure 2.

The detailed solution steps of the multi-objective optimization model are as follows.

- Initialize system parameters. Input daily PV power generation data and NSGA-III initial parameters, set upper and lower limits of decision variables and reference points on the hyperplane.
• Calculate the charging power of electric vehicles. Analyze the travel pattern of electric private cars and electric cabs, model their daily driving distance and starting charging time, count the number of electric vehicles charging in different time periods, and derive the daily load charging power curve of charging stations.

• Generate the initial population $P_t$. According to the operation mode of the storage charging station, the individuals in the population $P_t$ represent the magnitude of the charging and discharging power of the energy storage system at different times of the day, which can be expressed as:

$$P_t = \left[ P_{\text{Bess,1}}, \ldots, P_{\text{Bess,24}} \right]_{i=1,24}
\quad i = 1,2,\ldots,N$$  \hspace{1cm} (17)

Figure 2. Flow chart of multi-objective model solution

- Calculate the objective function value and perform fast non-dominated ranking. The function value of the optimization objective is calculated by bringing $P_t$ into Equations (5)-(10), and the fast non-dominated ranking of $P_t$ is performed according to the fitness of the objective function value.
- The first $N/2$ dominant individuals in $P_t$ were subjected to crossover mutation to obtain the offspring $Q_t$, and then $P_t$ and $Q_t$ were combined to obtain $R_t$. $R_t$ was subjected to fast non-dominance sorting, and the individuals in the non-dominance layer were put into the new population $S_t$ until the number of individuals in $S_t$ was greater than $N$.
- Adaptive normalization of the population individuals. Find the ideal points of each objective function in $S_t$, scalarize each objective function, secondly search the extreme value points of
each objective function to construct the hyperplane, and normalize the objective function according to the intercept of hyperplane and coordinate axis.

- Elite reservation. The top $N$ individuals from $S_i$ were selected as the parent population $P_{t+1}$ based on the objective function fitness value, the association between individuals and the reference point for non-dominated ranking.
- Termination condition. The number of iterations of the population is judged, and the optimization result is output if the termination condition is satisfied, otherwise it goes to the next cycle.

5. Analysis of calculation cases

5.1. Base data

In order to verify the rationality and effectiveness of the energy storage capacity optimization allocation model constructed in the paper, the base data are set as follows.

- The PV-integrated EV charging station adopts the DC fast charging mode, the number of charging piles in the station is 30, and the charging power of a single charging pile is 60kW. The rated capacity of the distribution transformer is 2MVA. The rated power of the AC/DC converter module is 1500kW.
- Assuming that the number of electric vehicles within the service area of the charging station is 500, among which the ratio of the number of electric private cars and electric cabs is 7:3, the daily charging load demand of the charging station is obtained by Monte Carlo algorithm simulation, and the power curve is shown in figure 3. The typical daily PV forecast data of a place is selected as the base data, and the PV output ratio is set to 18%, and the power curve is shown in Figure 4.
- The price of electricity purchased from the grid by the PV-integrated EV charging station adopts the price of electricity sold by the Shanghai power grid.
5.2. Analysis of optimization results

The multi-objective model simulation of energy storage system capacity is solved by MATLAB software, and the basic parameters of NSGA-III algorithm are set as follows: the initial population number $N$ is 200, the maximum number of iterations $Gen_{max}$ is 1000, the number of reference points is 190, and the crossover rate is 0.9. The capacity of energy storage system is optimized by combining PV output characteristics, load data and charging station operation mode to obtain The Pareto optimal solution set is shown in Figure 5.

As can be seen from figure 5, the solutions for the optimal capacity allocation of the energy storage system are uniformly distributed on the Pareto front, reflecting the diversity and convergence of the solution set, which can provide a large number of solutions for the conflicting objectives of the daily net revenue of the charging station and the peak-to-valley difference rate. If the decision makers give priority to the economics of charging station operation, it will be unfavorable to reduce the peak-to-valley difference rate; if the goal is only to reduce the peak-to-valley difference of the equivalent load on the grid side, it will greatly reduce the economic benefits of charging station operation. Therefore, it is necessary to weigh multiple interests, fully explore the Pareto frontier information, and objectively select the decision solution.

In order to further analyze the rationality of multi-objective optimal allocation of energy storage system capacity, the relationship between the rated power/rated power of the energy storage system and the daily net revenue and peak-to-valley differential rate of the charging station is analyzed in detail, as shown in figure 6.
As can be seen from Figure 6, on the basis of satisfying the charging load, as the daily net revenue of the charging station increases, the larger the energy storage capacity needs to be configured; meanwhile, the large-capacity energy storage device can further reduce the peak-to-valley difference rate on the network side. However, considering the conflicting interests of the two optimization objectives, in order to verify the rationality of the optimization objectives and constraints in the paper, three schemes with peak-to-valley difference rates of 30%, 45% and 60% are selected to complete the optimal allocation of energy storage capacity in the Pareto optimal solution set shown in Fig. 6, as shown in table 1.

### Table 1. Different energy storage system capacity configuration scheme

| Program Comparison | Scheme 1 | Scheme 2 | Scheme 3 |
|--------------------|----------|----------|----------|
| Peak-to-valley differential rate/% | 30       | 45       | 60       |
| Charging station daily revenue/RMB | 7911     | 8298     | 8635     |
| ESS rated power/kW | 980      | 787      | 752      |
| ESS rated capacity/kWh | 5789     | 4558     | 3820     |

As can be seen from table 1, station builders can take into account system economy and reliability, as well as various local influencing factors, and choose the most suitable local energy storage system configuration scheme, so that the overall performance of the optical storage charging station can be improved.

## 6. Conclusion

The paper researches the capacity optimization allocation method of energy storage system for PV-integrated EV charging station, and establishes a multi-objective optimal allocation model for energy storage capacity with the daily net revenue of charging stations and the peak-to-valley difference rate on the grid side as the optimization objectives. The NSGA-III algorithm is used to solve the optimal allocation model of energy storage capacity, which provides multiple allocation options for the optimization of energy storage system capacity on the basis of satisfying the load demand, and ensures the rationality of the optimization from the global perspective, which makes the overall performance of the charging station comprehensive and optimal, and provides technical support and the basis for the construction of integrated light-storage charging power station.

## 7. References

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