

## Research on Optimal Operation of Substation Self-consumption Load Considering Uncertainty

Lili Jiang <sup>1,a</sup>, Liang Kong <sup>1,b,\*</sup>, Xiaoqing Su <sup>1,c</sup>, Jiansheng Huang <sup>1</sup>, Yin Xia <sup>1</sup>

<sup>1</sup> State Grid Jiujiang Power supply company, Jiujiang 33200, China.

<sup>a</sup> jiangliliwonderful@126.com, <sup>b,\*</sup> k\_liang1993@163.com, <sup>c</sup> 2501800620@qq.com

**Abstract.** Under the goal of "double carbon", in order to reduce the power consumption, reduce the cost of carbon emission and increase the utilization rate of renewable energy, we propose the optimal operation method of substation self-powered load considering uncertainty. The optimal operation model of substation is established with the objective function of minimizing the operating cost, carbon emission cost and load power variance. The optimal operation strategy of the substation is solved by the affiliation function and particle swarm algorithm, and at the same time, the starting and stopping situations of each load of the substation are solved according to integer planning. A substation in Henan Province is analyzed as an example, and the results show that the method has obvious advantages in reducing the cost of electricity consumption, carbon emission cost, and peak-to-valley difference of the power grid when considering different objectives for optimization comparison under the consideration of photovoltaic and time-sharing tariffs.

**Keywords:** Substation; Dual carbon targets; Electricity cost; carbon emission.

### 1. Introduction

The situation of power supply in the peak summer (winter) is exceptionally severe. The annual self-consumption of electricity by the power supply company is about 0.5%. In order to achieve the goals of "carbon neutral" and "carbon peak", and to build an international leading energy internet enterprise with Chinese characteristics, how to save energy and reduce consumption has become a trend [1-2].

For the energy optimization problem considering uncertainty. Literature [3] proposes a robust optimization method to accommodate uncertainty in cooling, heating and electrical loads as well as PV output power. Literature [4] used robust optimization to deal with wind power uncertainty on the source side and load uncertainty on the load side through stochastic optimization, which takes into account the dispatch cost and reliability. Literature [5] investigated stochastic optimization of an integrated electricity-gas energy system based on an energy hub model and used Cornish-Fisher extension to incorporate chance constraints into the optimization, which transformed the stochastic problem into a deterministic one. Literature [6] modeled load uncertainty based on interval mathematics and developed an interval linear stochastic chance constrained planning model for day-ahead scheduling. Literature [7] used interval mathematics to characterize energy uncertainty and optimize with the objective of maximum efficiency and minimum operating. Existing researches have achieved some results in the field of energy optimal scheduling considering source-load uncertainty, but in general, researchers have mainly addressed the uncertainty problem from algorithmic processing and microgrid system of combined cooling, heating and power supply, and seldom considered the optimization strategy of photovoltaic-containing substation in time-of-day tariff environment specifically.

Under the goal of "double carbon", the optimal operation method of substation self-consumption load considering uncertainty is proposed for the goals of reducing power, reducing carbon emission cost and increasing renewable energy utilization. The optimal operation model of substation is established with the objective function of minimizing the operating cost, carbon emission cost and load power variance. The optimal operation strategy of the substation is solved by the affiliation function and particle swarm algorithm, and at the same time, the starting and stopping situations of the substation load are solved according to the integer planning algorithm. The results are analyzed as an arithmetic example of a Vigilance station in Henan Province, and the results show that the

optimization is carried out and compared for different objectives under the consideration of photovoltaic and time-sharing tariffs.

## 2. Smart Power Optimization Model with Photovoltaic Substation

### 2.1 Photovoltaic and Load Uncertainty Modeling

Controllable loads such as substation air conditioners and dehumidifiers and photovoltaic (PV) power generation introduce uncertainty, and in this paper, modeling is carried out through the multi-scenario technique, which is a method for describing stochastic processes that transforms load and PV forecasts containing uncertain errors into deterministic sets of scenarios, allowing subsequent dispatch to include consideration of different error levels while simplifying calculations. Uncertainty modeling consists of two parts: scenario generation and scenario reduction.

#### 2.1.1 Scene Generation

In this paper, latin hypercube sampling (LHS) is used to generate the load and PV output scenarios, and compared to Monte Carlo simulation, LHS is able to ensure that all the sampling area is covered by sampling points through stratified samplin. Stochastic optimization problems can be transformed into deterministic optimization problems through scenario generation.

#### 2.1.2 Scene Cuts

In order to get rid of the dependence of the traditional clustering algorithm on the number of selected target scenes  $K$ , an improved hierarchical K-means clustering algorithm based on the maximum distance method is proposed, the initial value of clustering is selected by the maximum distance method, and the best clustering center is obtained by the hierarchical K-means clustering algorithm. Taking PV output as an example, the steps of scene reduction algorithm are as follows.

Step 1: Let a total number of valid days of data  $M$  be acquired, the original set of scenarios for PV output be  $\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_M]$ , the vector of any scenario power data be  $\mathbf{P}_i = [p_{i,1}, p_{i,2}, \dots, p_{i,T}]$ , and the number of initial clusters be set to  $K_1$ .

Step 2: Select  $K_1$  initial clustering centers based on the maximum distance method as follows.

Step 2.1: Select the 2 scenes with the largest distance in the scene set as the initial clustering center, and the scene distance  $d$  is calculated as

$$d_{\mathbf{P}_i, \mathbf{P}_j} = \sqrt{\sum_{t=1}^T (p_{i,t} - p_{j,t})^2} \quad (1)$$

Step 2.2: Among the remaining  $M-2$  scenarios, select the scenario with the largest distance product to the previous 2 initial scenarios as the third clustering center; in this way, we get the  $K_1$  initial clustering centers.

Step 3: Perform K-means clustering, assign all scenes to the nearest clustering centers, make the number of iterations  $l=1$ , and calculate the value of the  $l$ th clustering metric function  $J^{(l)}$ , the clustering metric function is calculated as

$$J = \sqrt{\frac{\sum_{i=1}^K \sum_{j=1}^{M_i} (\mathbf{P}_i^j - \mathbf{C}_i)^2}{M-1}} \quad (2)$$

In this formula:  $M_i$  is the number of scenes in the  $i$ th class,  $\mathbf{P}_i^j$  is the  $j$ th data vector in the  $i$ th class;  $\mathbf{C}_i$  is the clustering center of the  $i$ th class.

Step 4: Carry out the next level of clustering, the specific steps are as follows.

Step 4.1: Select the class with the largest radius among all clusters, and the class radius is calculated as

$$r_i = \max \| \mathbf{P}_j - \mathbf{C}_i \|, j = 1, 2, \dots, M_i \quad (3)$$

Step 4.2: Select the 2 scenes with the largest distance in the class as the new clustering center.

Step 4.3: Re-perform K-means clustering based on the clustering centers, so that  $l = l + 1$ , and calculate the value of the  $l+1$ th clustering measure function  $J^{(l+1)}$ .

Step 5: Define  $\varepsilon = (J^{(l)} - J^{(l+1)}) / J^{(l)}$ , if  $\varepsilon > \varepsilon_0$ , then return to step 4 to continue iteration, where  $\varepsilon_0$  is a given threshold, which can be set according to the clustering measurement function value change curve; otherwise the algorithm ends and outputs the number of clustering centers and clustering results.

Step 6: Calculate the probability of occurrence and clustering center for each scenario of PV output after reduction.

## 2.2 objective function

Objective function (1): Minimal electricity cost for substations  $f_1$ , which consists of: the cost of purchasing electricity  $C_s$ , photovoltaic operating costs  $C_{PV}$ , battery operating costs  $C_{Bt}$ , and electricity sales revenue  $I_{an}$ .

$$\min f_1 = \sum_{k=1}^K \pi_k (C_s + C_{PV} + C_{Bt} - I_{an}) \quad (4)$$

$$\text{Where } C_s = \sum_{i=0}^{23} J_s(t_i) P_s(t_i) \quad ; \quad C_{PV} = \sum_{i=0}^{23} J_{PV}(t_i) P_{PV}(t_i) \quad ; \quad C_{Bt} = \sum_{i=0}^{23} J_{Bt}(t_i) |P_{Bt}(t_i)| \quad ;$$

$I_{an} = \sum_{i=0}^{23} J_{an}(t_i) P_{net}(t_i)$ ;  $\pi_k$  is the probability value of the occurrence of the scenario  $k$ .  $J_s(t_i)$  is electricity purchase price from the power plant at the time of  $t_i$ ;  $P_s(t_i)$  is consumption of grid power at the time of  $t_i$ ;  $J_{PV}(t_i)$  is the unit operating cost of the PV array at the time of  $t_i$ ;  $P_{PV}(t_i)$  is the generating power of the PV array at the time of  $t_i$ ;  $J_{Bt}(t_i)$  is the unit maintenance cost of the batteries;  $P_{Bt}(t_i)$  is the charging power of the batteries at the time of  $t_i$ ; the power of the batteries at the time of discharging is positive, and the power of the batteries at the time of charging is negative;  $J_{an}(t_i)$  is the price of the electricity at the time of  $t_i$ ;  $P_{net}(t_i)$  is the power of the grid connection at the time of  $t_i$ ;

Objective function (2): In response to the call for a "dual-carbon" target, the operation should consider minimizing system carbon emissions. When developing the dispatch plan, priority should be given to photovoltaic power generation by means of multi-energy complementary means, and then power should be obtained from the grid. Carbon emissions are minimized:

$$\min f_2 = \sum_{k=1}^K \pi_k \sum_{i=0}^{23} \beta_{grid} P_s(t_i) \quad (5)$$

Where  $\beta_{grid}$  denotes the carbon emission factor generated by purchasing a unit of electricity from the public grid.

Objective function (3): minimize the grid load power mean squared error with

$$\min f_3 = \sum_{k=1}^K \pi_k \sum_{i=0}^{23} (P_L(t_i) + \sum_{j=1}^n P_{sj}(t_i) - P_{av})^2 \quad (6)$$

Where  $P_L(t_i)$  is the power value of the load at the time of the grid  $t_i$ ;  $P_{sj}(t_i)$  is the input power value of the grid side of substation  $j$  at the time of  $t_i$ ;  $P_{av}$  is average power,  $P_{av} = \sum_{j=1}^n (P_L(t_i) - \sum_{i=1}^n P_{sj}(t_i)) / 24$ .

$$\text{In summary} \quad \min f = \{f_1, f_2, f_3\} \quad (7)$$

### 2.3 Constraints

The constraints on the power used in the substation of the PV-containing system include:

(1) Electrical power balance constraints.

When charging, there is

$$P_s(t_i) + P_{PV}(t_i)\eta_{PV} + \frac{P_{Bt}(t_i)}{\eta_{Bt}} - P_{net}(t_i) - P(t_i) = 0 \quad (8)$$

When discharged, there is

$$P_s(t_i) + P_{PV}(t_i)\eta_{PV} + P_{Bt}(t_i)\lambda_{Bt} - P_{net}(t_i) - P(t_i) = 0 \quad (9)$$

In this formula  $\eta_{PV}$  is the PV power generation efficiency;  $\eta_{Bt}$  is the battery charging efficiency;  $\lambda_{Bt}$  is the battery discharging efficiency.

(2) Battery operation constraints.

$$P_{ch}^{max}(t_i) \leq P_{Bt}(t_i) \leq P_{dis}^{max}(t_i) \quad C_{soc}^{min} \leq C_{soc}(t_i) \leq C_{soc}^{max} \quad \sum_{i=0}^n P_{Bt}(t_i)\Delta t = 0 \quad (10)$$

In this formula  $P_{ch}^{max}(t_i)$  and  $P_{dis}^{max}(t_i)$  are the maximum power of battery charging and discharging respectively;  $C_{soc}^{min}$  and  $C_{soc}^{max}$  are the minimum and maximum capacity of battery operation.

(3) Grid-side exchange power constraints

$$0 \leq P_s(t_i) \leq P(t_i)^{max} \quad 0 \leq P_{net}(t_i) \leq P_{PV}(t_i) \quad (11)$$

In this formula  $P(t_i)^{max}$  is the maximum power value from the grid side.

## 3. Model fuzzification and solving

### 3.1 Fuzzification of the model

The equation (7) of the objective function of the substation smart power optimization operation belongs to the multi-objective optimization problem, the optimal solution of multi-objective is related to the solution of each sub-function. The PSO solves the substation optimization fuzzification model to derive the optimal operation strategy of the substation bank.

In this paper, the operation cost and load change of substation is minimized as the goal, the smaller the target, the larger the affiliation value, where the value of affiliation function  $\mu(t_i)$  1 indicates the most satisfactory, 0 indicates unsatisfactory, the comprehensive needs of all aspects of this paper to select the bias small drop half  $\Gamma$  type distribution.

$$\mu_k(t_i) = \begin{cases} 1 & f_k \leq f_k^{min} \\ \exp\left(\frac{f_k^{min} - f_k}{f_k^{min}}\right) & f_k > f_k^{min} \end{cases} \quad (13)$$

Where  $f_k^{min}$  is the minimum value of  $f_k$  at the corresponding constraint,  $k=1,2,3$ .

### 3.2 Solving substation load turning problem based on integer programming

For each type of air conditioner and dehumidifier in the substation and other specific load start and stop situation to solve, transformed into an integer planning problem, the model of the independent variables are all integers, and the independent variables take the value of 0 and 1, that is, represents the switching state of the various loads, constraints for the various loads in the substation operating characteristics and operating requirements; The objective function is to minimize the difference between the total power of the load and the ideal power at that time, the It is expressed as

$$\min \varepsilon = \sum_{j=1}^n P_j(t_i)x_j - P(t_i) \quad (15)$$

The constraints are Eqs. (8) to (13). The individual load start-stop situation is calculated using the lingo software, and the start-stop of each switch is controlled through the intelligent controller.

#### 4. Example analysis

This paper takes a substation in Henan as an example, and analyzes the optimal operation of the substation through PSO algorithm. The optimal temperature range of the substation is 18°C~28°C, especially, the substation does not need to turn on the air conditioner in the high-voltage room and the relay room in winter.

The load and PV combination generates 1000 load scenarios, and the scene reduction is carried out by the improved hierarchical K-means algorithm, and the scene set and the probability of occurrence of the scene are obtained as shown in Fig. 3, and the magnitude of the variability between different scenarios reflects the level of accuracy of the prediction a few days ago. In Fig. 3, the data in the center is the probability value of the occurrence of the scene.

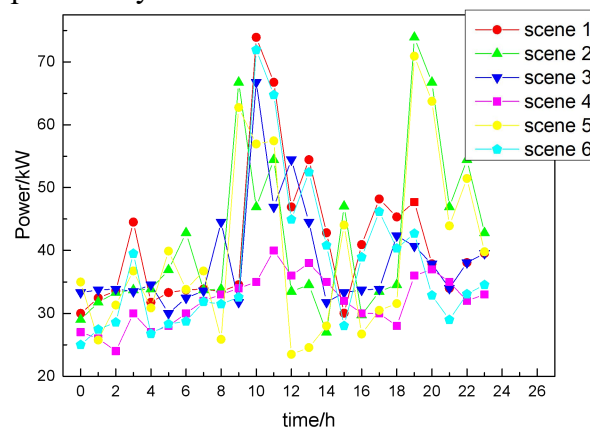


Fig. 3 Typical set of scenarios

The model of this paper is solved by PSO algorithm. The data involved in the model calculations are obtained through research, Henan electricity price and feed-in tariffs, which are as follows:  $\lambda_{PV} = \eta_{Bt} = \lambda_{Bt} = 0.9$ ;  $P_{net}^{max}(t_i) = 56.16kW$ ;  $P^{max}(t_i) = 76.1kW$ ;  $J_{an} = 0.62yuan / kWh$ .

In order to analyze the multi-objective optimization model as well as to consider the reasonableness and effectiveness of uncertain scenarios, this paper sets up four optimization algorithms for comparative analysis.

Example 1: No strategy is used. Example 2: Load power rms variance is not considered and the goal is to minimize the desired operating costs and carbon emissions. Example 3: No operating costs are considered and the goal is to minimize load power rms and carbon emissions. Example 4: Carbon emissions are not considered and the objective is to minimize the operating cost and load power mean square error. Example 5: Combining operating costs, carbon emissions and load power rms.

The optimization results are shown in Table 1.

Table 1. Optimization results for different examples

example	Running costs (¥)	Carbon emissions (kg)	Load Power Mean Square Error
1	348.34	651.06	142
2	283.35	530.52	179
3	376.15	649.15	102
4	331.33	674.15	109
5	309.78	603.24	145

Through the above calculation results, we get different optimization results for different calculation objectives, depending on the focus of our optimization results. For the substation load,

the main focus is on carbon emission and operation cost, which is the result of example 2. The cost saving is 18.66% and the carbon emission saving is 18.51%. By adding the control strategy, we can save the cost of electricity and reduce the carbon emission.

According to the calculation of example 2 to get the substation load power situation, considering the summer and winter power load opening situation is different, for the substation of different loads with different situations, the load level can be expressed as process 1 ~ process 5, through the integer planning algorithm to calculate the substation load opening situation, as shown in Figure 4, detailed individual loads actually open the situation is not to repeat.

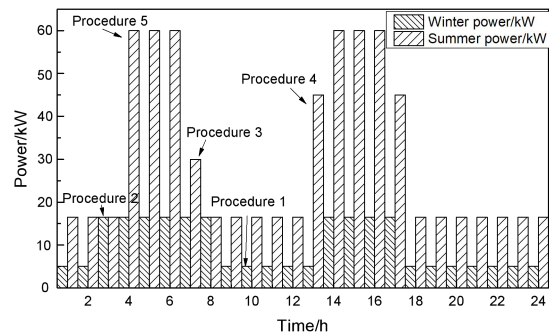


Fig. 4 Open load of cold storage at different times step

## 5. Summary

(1) This paper analyzes the optimal operation of substation self-consumption loads by considering uncertainty, establishes a multi-objective optimal operation strategy with minimum operation cost, carbon emission and grid load fluctuation. Finally, each load control strategy of the substation is obtained according to integer planning.

(2) Taking a substation in Henan as an example, we comprehensively compare the optimized operation of the substation under each objective. It also compares different focusing objectives and shows that the use of control strategy can reduce the operation cost, carbon emission or peak-valley difference.

This project is supported by the technology project of State Grid Jiangxi Electric Power Company, and the research on non-invasive smart energy management technology for self use electricity under the "dual carbon" goal (5218D023000B).

## References

- [1] Yuan Yalin. Optimal allocation method of wind-solar hybrid system capacity in the context of energy saving and emission reduction[J]. Energy and Energy Conservation,2022(05):71-73.
- [2] Li Xiaopeng,Cheng Xiaolei,Cai Wenbin et al. Comprehensive evaluation method of energy saving, emission reduction and operational efficiency of power grid under carbon neutral target[J]. Electrotechnology,2022(02):15-17.
- [3] Luo Zhao, Gu Wei, Wu Zhi, et al. A robust optimization method for energy management of CCHP microgrid[J].Journal of Modern Power Systems and Clean Energy. 2018, 6(1):132-144.
- [4] Zhu Lan, Wang Ji, Tang Longjun, et al. Robust stochastic optimal dispatching of integrated energy systems considering refined power-to-gas model[J]. Power System Technology, 2019, 43(1): 116-125.
- [5] Qadrdan M, Wu Jianzhong, Jenkins N, et al. Operating strategies for a GB integrated gas and electricity network considering the uncertainty in wind power forecasts[J].IEEE Transactions on Sustainable Energy, 2014, 5(1):128-138.
- [6] Huo Da, Gu Chenghong, Ma Kang, et al. Chance-constrained optimization for multienergy hub systems in a smart city[J].IEEE Transactions on Industrial Electronics, 2019, 66(2):1402-1412.

- [7] Jiang Yefeng, Zhou Haiqiang, Luo Jianyu, et al. Day-ahead optimal dispatch of power system considering source and load interval uncertainties[J]. Electric Power Engineering Technology, 2022, 41(4):58-66.