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Distribution Network Double-Layer Optimization Strategy Based on Distributed Generation

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Abstract. The increasing use of renewable energy in the distribution network has led to several issues such as large load flow calculation and frequent overvoltage, making it challenging to ensure the quality of power supply. This paper presents a two-level optimization strategy that leverages the cooperation of distributed power supply and active distribution network to address these challenges. The upper-level model aims to minimize distribution network loss, improve voltage stability, and reduce the total cost of network operation. The lower-level model focuses on coordinated control of distributed power supply and other devices to enhance user demand response and ensure real-time dispatching reliability. To solve the model, this paper utilizes an improved binary particle swarm optimization (BPSO) and genetic algorithm (GA) based on the model's characteristics. The results demonstrate that the proposed bi-level optimization method effectively enhances voltage distribution and smooths the load peak-valley difference.

Keywords. Active distribution network, distributed power supply, bi-level optimization, particle swarm optimization algorithm, load peak valley

1. Introduction

In recent years, micro-grids have emerged as a promising solution for utilizing distributed power sources such as wind power and photovoltaic, which can absorb renewable energy locally and reduce power generation costs [1-3]. However, the intermittence and randomness of distributed generation pose significant challenges to the safe and reliable operation of distribution networks. To address this issue, researchers are focusing on the development of Active Distribution Networks (ADN), which are designed to accommodate large-scale distributed generation, feature flexible topology, and enable active regulation of resources on both sides of supply and demand. The key challenge now is to balance the power quality of distributed generation with the acceptance capacity and management level of ADN, which remains a critical area of research [4-6].

In the active distribution network system with distributed generation, the distributed generation has the attributes of controllable power supply or controllable load. It needs to interact with the active distribution network continuously, which will affect the power flow calculation of the distribution network and further affect the safety and economy of

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the active distribution network [7-8]. At present, domestic and foreign scholars believe that distributed generation has more influence on the control architecture, optimal scheduling method and coordinated operation planning of active distribution network system. In Reference [9],a bi-level optimization model of distributed generation and ADN is established based on the time-of-use electricity price mechanism, and the influence of distributed generation mode on the economy and reliability of ADN system is considered. Reference [10] constructed a bi-level optimization model based on Stackelberg game for different benefit evaluation indexes of charging station and distributed generation system. Based on the difference of electricity price in different time periods, Reference [11] proposed a joint optimization scheme considering the interaction of microgrid group. The optimal benefit of microgrid group was taken as the optimization objective, and the mathematical model was established according to the joint optimization scheme. Reference [12] solved the ADN network by using a two-layer nested optimization scheduling method. The upper layer aims at minimizing voltage fluctuations, and the lower layer aims at minimizing distributed generation costs to improve system reliability and reduce wind and light curtailment. Reference [13] established a microgrid scheduling strategy, which divides the management system into two layers. The remaining or insufficient power of the inner microgrid is used as the power supply or compliance of the outer microgrid. Compared with the traditional energy management strategy, the microgrid group under the hierarchical management mode has lower operating costs.

This paper proposes a bi-level optimization strategy based on the coordinated control of distributed generation and active distribution networks. The upper model aims to minimize distribution network losses, achieve the highest voltage stability, and minimize overall operational costs. The lower model focuses on the coordinated control of distributed generation and other equipment to improve user demand response and ensure reliable real-time power grid dispatching. The two-layer model will interact with energy flows via the common connection point to participate in scheduling decision-making and maximize ADN benefits. The proposed method uses a combination of improved binary particle swarm optimization and genetic algorithms to solve the model. The example analysis demonstrates that this approach can achieve a more reasonable scheme while effectively reducing system network loss and node voltage deviation, ultimately improving economic benefits and the power quality of the active distribution network.

2. Bi-level optimization framework

Bi-level optimization is generally used to solve complex models [14-15]. The bi-level optimization problem includes two levels of optimization tasks, one of which is nested in another optimization task. The two levels have their own goals and constraints and decision variables. In this paper, the two-layer optimization theory is used to study the upper and lower layers of ADN after it is incorporated into the distributed power grid system. The minimum loss of regional distribution network, the highest voltage stability and the lowest total cost of distribution network operation are taken as the objectives, and the output and regulation of distributed generation and equipment are considered to achieve the optimization objectives. The bi-level optimization model is shown in Figure 1.

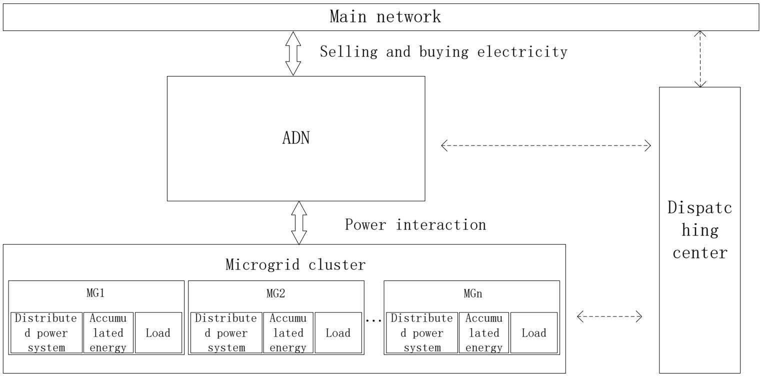

Figure 1. Bi-level optimal scheduling model of active distribution network

3. Bi-level scheduling model establishment

3.1 Upper optimization model

The objective function of the upper model includes multiple objectives such as line active power loss, static voltage stability index and total operating cost of the distribution network system, which can be transformed into a single objective function by normalized addition. The specific expression is as follows:

$$\min F_{up} = \beta_w F_w + \beta_v F_v + \beta_s F_s + F_{low} \tag{1}$$

F_w is the total network loss function of the distribution network in the scheduling period. , F_v is the mean value function of static voltage stability index in the scheduling period. , F_s is the distribution network cost function, F_{low} is the lower level optimization result. β_w , β_v , β_s is the weight coefficient.

The expression of the total network loss function F_w of the distribution network is as follows:

$$F_w = \min \sum_{t=1}^{24} \sum_{a=1}^{n_a} R_a \frac{P_a^2(t) + Q_a^2(t)}{V_a^2(t)} \Delta t \tag{2}$$

The period is 24, n_a is the total number of branches, R_a is branch a resistance, $P_a(t)$, $Q_a(t)$ are the active and reactive power flowing through line a at time t, respectively. , $V_a(t)$ is the voltage of branch a at time t.

The mean function F_v of the static voltage stability index in the scheduling period is expressed as follows:

$$F_v = \sum_{t=1}^{T} \frac{VSI(t)}{T} \tag{3}$$

$VSI(t)$ represents the static voltage stability index function of the system at time t.

$$VSI(t) = \max\{VSI_1(t), VSI_2(t), VSI_3(t)...VSI_{n-1}(t)\} \quad (4)$$

$$VSI_n(t) = 4[(X_{ij}P_j(t) - R_{ij}Q_j(t))^2 + (X_{ij}Q(t) + R_{ij}P_j(t))V_i^2(t)]V_i^4(t) \quad (5)$$

where n is the total number of nodes, P_j and Q_j are the active power and reactive power of node j, R_{ij} and X_{ij} are the resistance and reactance of branch i, and V_i is the voltage of node i.

The expression of distribution network operation cost function F_s is as follows:

$$F_s = \sum_{t=1}^{T} f_g + \sum_{t=1}^{T}\sum_{S=1}^{S} f_{DGS} \quad (6)$$

Among them, f_g is the cost of purchasing electricity from the distribution network to the main network, f_{DGS} is the operating cost of controllable distributed generation connected to the distribution network, f_g and f_{DGS} expressions are as follows :

$$f_g = C_g P_g(t) \quad (7)$$

$$f_{DGS} = A_s P_{DGS}(t)^2 + B_s P_{DGS}(t) + C_s \quad (8)$$

Where C_g is the transaction price between the distribution network and the upper main network, $P_g(t)$ is the amount of electricity purchased by the distribution network from the main network at time t, A_s and B_s are the total weight coefficients, C_s is a constant.

3.2 Lower level optimization model

The lower layer model takes the coordinated control of distributed power supply and other equipment as the goal, fully considers the load flexibility under the price incentive, saves the cost of electricity consumption and improves the stability and reliability of the distribution network without reducing the user experience. The specific expression is as follows:

$$F_{low} = C_{Dps} f_{Dps} + C_{DEM} f_{DEM} \quad (9)$$

f_{Dps} is the total output function of distributed generation, and f_{DEM} is the demand responsiveness. C_{Dps} and C_{DEM} represent the corresponding function coefficients respectively.

The output function expression of distributed generation is as follows:

$$f_{Dps} = \sum_{t=1}^{T} (k_{pv}P_{pv}(t) + k_{wt}P_{wt}(t) + k_{mt}P_{mt}(t) + k_{si}\,|\,P_{si}(t)\,|)\Delta t \quad (10)$$

$P_{pv}(t)$, $P_{wt}(t)$, $P_{mt}(t)$, $P_{si}(t)$ represent the predicted output of photovoltaic, wind turbine, micro gas turbine and energy storage power generation respectively. k_{pv} , k_{wt} , k_{mt} , k_{si} represent the corresponding output coefficients respectively.

The demand responsiveness expression is as follows:

$$f_{DEM} = \frac{1-\sum_{t=1}^{T}\sum_{n=1}^{N_b}|P_{n,t}^{N}|}{\sum_{t=1}^{T}\sum_{n=1}^{n_b}P_{n,t}^{D}} \tag{11}$$

$P_{n,t}^{N}$ represents the change of demand measurement response at n node t, and $P_{n,t}^{N}$ represents the total load before demand measurement response at n node t.

4. Model solving method

4.1 Model solving algorithm

In this paper, the particle swarm optimization algorithm is used to solve the upper and lower models respectively. The particle swarm optimization algorithm is derived from the complex adaptive system. It is a random search algorithm based on group cooperation developed by simulating the foraging behavior of birds. The optimal solution is found through continuous iteration of particles [16-19].

4.2 Introduction of genetic algorithm

The particle 's ' premature ' problem is a very common problem in particle swarm optimization. In the process of iterative solution, it is easy to fall into local optimum and cannot obtain the global optimal solution. By introducing genetic algorithm, a new total group is generated to enhance the global solution ability, so as to solve the problem of falling into local solution [20-21].

5. Example analysis

The improved IEEE-33 node distribution system is used as a simulation test example, and the relevant parameters in the original standard example of the system are used as a reference, as shown in Figure 2.

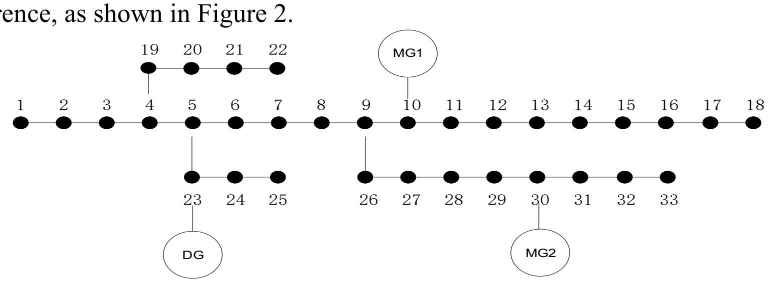

Figure 2. IEEE 33-bus active distribution network system diagram

A micro gas turbine and two microgrids are connected to the system. The maximum output of gas power generation is 180kW, and the DG access node of gas unit is 23. Two microgrids MG1 and MG2 are connected to nodes 10 and 30 respectively. Each microgrid contains a wind turbine, a photovoltaic unit, a diesel engine and an energy storage battery pack.

Set the distributed power parameters as table 1; the time-of-use electricity price of electricity sales and purchase in microgrid and active distribution network is shown in table 2.

Table 1. Distributed power supply parameters

Type	Photovoltaic	Wind turbine	Diesel	Battery
Power rating/kW	350	380	240	150

Table 2. Time-of-use electricity price table for microgrid and active distribution network

Type	Valley period	Usual period	Peak period
Time frame	0:00-8:00 18:00-24:00	8:00-11:00 16:00-18:00	11:00-16:00
Electricity purchase price / yuan· kWh-1	0.55	0.75	0.95
Electricity sales price / yuan· kWh-1	0.45	0.65	0.85

(1) The active distribution network does not participate in the microgrid layer scheduling, that is, the microgrid is not connected to the ADN. The microgrid group calculates the network loss and microgrid layer cost according to each output, and adjusts the power parameters of the corresponding nodes of the distribution network according to the power interaction index of the microgrid group, so as to calculate the network loss and operating cost of the distribution network, including the power purchase cost of the distribution network to the upper main network.

(2) For the bi-level optimization model proposed in this paper, that is, the microgrid is connected to the ADN, and the upper-level target requirements of the minimum distribution network loss, the highest voltage stability, and the lowest total operating cost of the distribution network are considered. The cost function of the lower microgrid group is iterated one by one and fed back to the upper function. The improved binary particle swarm optimization algorithm and genetic algorithm are combined to obtain the fitness function value of the subject, and finally the convergent scheduling scheme and total cost are obtained.

According to the above two schemes, the comparison of the purchase power of the active distribution network to the superior main network is analyzed. As shown in figure 3, it can be seen that in the peak period, under the scheduling scheme of micro-grid access to ADN, the purchase power of the distribution network to the main network is significantly smaller than that without access, while in the normal period and the valley period, the purchase power is more than that of the first scheme. It shows that after the micro-grid is connected to the ADN, the micro-grid fully participates in the coordination of electricity consumption, which makes the active distribution network system play a more obvious role in peak load shifting of the main network.

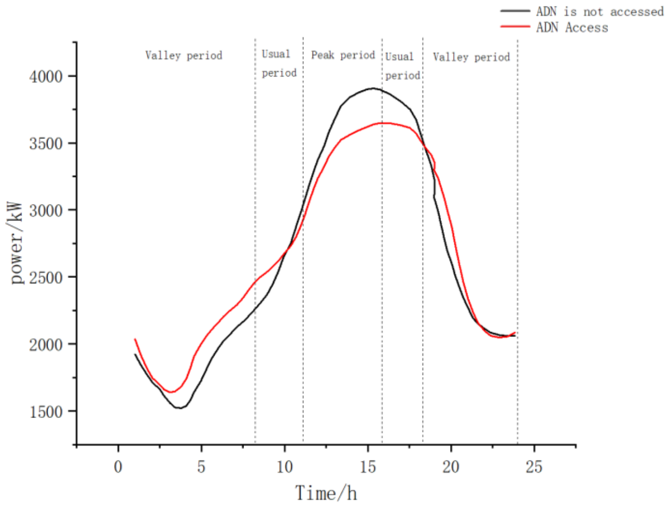

Figure 3. The relationship between the active distribution network to the main network to buy electricity and time period

The network loss change of the active distribution network is shown in Figure.4.It can be seen from the network loss change curve of the active distribution network that, especially at the peak load of high electricity bills, compared with the case where the micro-grid is not connected to the ADN, the network loss of the distribution network that has been connected to the micro-grid and participated in the regulation has been significantly improved. Due to the coordinated control of the micro-grid group, the distribution network purchases less electricity from the main network during the peak period, and the micro-grid fully participates in the power demand of the distribution network at this stage, which well stabilizes the peak and valley of the power grid.

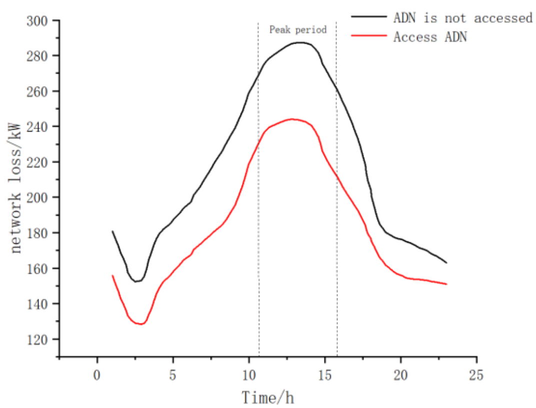

Figure 4. Network loss curve of active distribution network

The ADN power generation cost is shown in Figure 5. When the microgrid sells electricity to the ADN, the ADN system can reduce its own unit output and reduce the power generation cost during the peak period. The power purchase cost of the microgrid group not connected to the ADN is much higher than the access cost. In the example, the two microgrids have more periods of time to sell electricity to the ADN and the power sales are larger. Therefore, the overall power generation cost of the ADN system connected to the multi-microgrid in Figure 5 is smaller than that of the ADN not connected to the multi-microgrid.

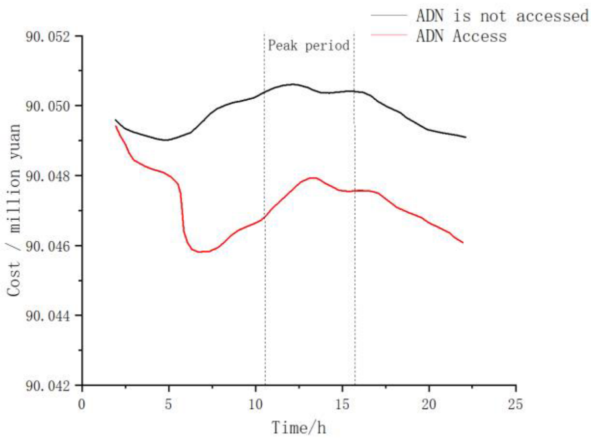

Figure 5. ADN system power generation cost comparison curve

6. Conclusion

The paper proposes a two-layer optimization model to address the network loss and power quality issues that arise from connecting various distributed power sources to the active distribution network. The upper model targets minimizing distribution network loss, achieving the highest voltage stability, and reducing overall operational costs. The lower model focuses on coordinated control of distributed power sources and other equipment, aims to enhance user demand response capability, and ensure reliable real-time power grid scheduling. The improved binary particle swarm optimization and genetic algorithm are utilized to solve the model. The improved IEEE33 node system is used as a simulation verification case. The simulation outcomes demonstrate that the proposed bi-level optimization strategy effectively reduces network loss and operational costs of the active distribution network, suppresses system node voltage drop, enhances system power quality, improves voltage distribution of the distribution network, and stabilizes peak-valley load differences.

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