Active and reactive power joint optimization of active distribution network under new energy access

Wei Wei1,a, Zhang Jiangbin1, Yang Zhao1, Ma Zihan1
1Xi’an University of Technology, Xi’an710048, China
avivi66912@163.com

Abstract. The access of large-scale distributed generation (DG) to the active distribution network has a great influence on the power flow, node voltage and network loss of the distribution network. In this paper, in order to improve the operation level and economic performance of the active distribution network, the distributed power supply reactive power output and load reduction are used as control variables to establish a multi-objective optimization model with the total network loss, voltage deviation and load reduction cost as the objective function. The voltage of each node, system network loss, load reduction cost and their corresponding control variables are calculated by improved simulated annealing multi-objective particle swarm optimization algorithm. Finally, the IEEE33 node system is used for example verification, the results show that the mathematical model can achieve coordinated control of voltage, reduce network loss and meet the requirements of actual power grid operation.

1. Introduction
Active distribution network (ADN) is based on appropriate supervision system and user access criteria to actively control DG, energy storage unit and controllable load. ADN uses flexible network topology to adjust power flow distribution reasonably, so that distributed energy can provide a certain degree of support to the distribution network. Improving the operation level and economic performance of the active distribution network through reactive and active optimization is one of the important ways to ensure the reliable and safe operation of the power grid. At present, there have been many studies on the optimal dispatch of active distribution networks. Nick [1] studies the optimization problems of tap-changers and energy storage equipment, considered the intra-day situation in advance, and used the enumeration method to deal with the uncertainty of electricity prices and light charges. X.L.Su [2] proposes an ADN coordinated control method that combines global centralized optimization and regional decentralized autonomy, global optimization gives the exchange power plan value of each area, regional autonomy is based on the feedback controller to adjust the component output, but the reactive power in ADN is not considered in this article. Y.Fu [3] introduces a semi-invariant method for stochastic power flow, which takes into account the risk of over-limits caused by the forecast errors of new energy output in the dispatch of the distribution network, and considers the economics and safety of dispatch at the day-ahead stage. F.X.Meng [4] takes into account the uneven distribution of controllable resources in different regions, and proposes an active and reactive power coordination and optimal scheduling model for active distribution networks considering regional autonomy. KINHEKAR [5] proposed an ADN two-stage scheduling strategy, day ahead scheduling is economic dispatch and intra-day scheduling uses controllable DG active power for rolling correction, but this method failed to effectively solve the problem of voltage overrun. Taking into account the uncertainty of renewable
energy, H.J.Gao [6] and J.W.Liang [7] used a robust model to describe the uncertainty of renewable energy and established a distributed energy management model for the active distribution network.

It can be seen from the above literature that most of the optimized dispatching of active distribution networks at this stage is to optimize dispatching unilaterally from reactive power or active power in the control grid. The line impedance ratio in the actual power grid is large, and with the access of distributed power, its active and reactive power output have become important factors that affect the voltage level and power flow distribution. Therefore, active and reactive power play a vital role in the safety and stability of the distribution network, single reactive power control and active power control can no longer meet the needs of current distribution network development. In view of the above problems, this paper studies the active and reactive power joint optimization of the active distribution network. The improved simulated annealing multi-objective particle swarm optimization algorithm is used to solve the related control variables to achieve the optimization goal of minimum network loss, voltage deviation and load reduction, and improve the operating level of each node voltage. Finally, an example is used to verify the effectiveness of the proposed method, and multiple optimization schemes are obtained, it is proved that the optimization strategy proposed in this paper is more feasible and flexible.

2. Multi-objective reactive and active joint optimization model of active distribution network with DG

2.1. Objective function

1) Active loss

\[
f_1 = P_{\text{loss}} = \sum_{i,j \in N_j} G_{ij} (U_i^2 + U_j^2 - 2U_i U_j \cos \theta_{ij}) \tag{1}
\]

Where:
- \( P_{\text{loss}} \) represents the total active power loss of the system;
- \( U_i \) represents the voltage at node \( i \);
- \( U_j \) represents the voltage at node \( j \);
- \( G_{ij} \) represents conductance value of branch between node \( i \) and node \( j \);
- \( \theta_{ij} \) represents the voltage phase angle difference between node \( i \) and \( j \) node.

2) Node voltage deviation

\[
f_2 = \Delta U = \sum_{i=1}^{N_j} \left| \frac{U_i - U_i^*}{U_{i,\text{max}} - U_{i,\text{min}}} \right| \tag{2}
\]

Where:
- \( \Delta U \) represents the total voltage deviation of distribution network;
- \( U_i^* \) represents the node \( i \) rated voltage;
- \( U_{i,\text{max}} \) represents node \( i \) maximum allowable voltage;
- \( U_{i,\text{min}} \) represents node \( i \) minimum allowable voltage;
- \( N_j \) represents node number.

3) Load reduction cost

\[
f_3 = \sum_{i=1}^{N_{\text{user}}} P_{i,\text{cut}} \cdot \rho_{i,\text{cut}} \tag{3}
\]

Where:
- \( P_{i,\text{cut}} \) represents the user \( i \) load reduction;
- \( \rho_{i,\text{cut}} \) represents the user \( i \) unit load reduction cost;
- \( N_{\text{user}} \) represents the number of users participating in load reduction.

Combining the three objectives of network loss, node voltage deviation and load reduction cost, the total objective function is as follows:

\[
F = \min(f_1, f_2, f_3) \tag{4}
\]

2.2. Constraint condition

1) Equality constraints
The mathematical model of the active and reactive power injection into the node is given by the following equations:

\[
\begin{align*}
P_i &= \sum_{i \in N_{sup}} P_{sup,i} + \sum_{i \in N_{wt}} P_{wt,i} + \sum_{i \in N_{pv}} P_{pv,i} - \sum_{i \in N_{load}} P_{load,i} \\
Q_i &= \sum_{i \in N_{sup}} Q_{sup,i} + \sum_{i \in N_{wt}} Q_{wt,i} + \sum_{i \in N_{pv}} Q_{pv,i} - \sum_{i \in N_{load}} Q_{load,i}
\end{align*}
\]  

(5)

Where: \(N_{sup}\), \(N_{wt}\), \(N_{pv}\) and \(N_{load}\) are superior grid access node, wind power access node, photovoltaic power access node and user load access node; \(P_i\), \(P_{sup,i}\), \(P_{wt,i}\), \(P_{pv,i}\) and \(P_{load,i}\) are active power inject into node \(i\), superior grid inject active power, wind power inject active power, photovoltaic power inject active power and active load value; \(Q_i\), \(Q_{sup,i}\), \(Q_{wt,i}\), \(Q_{pv,i}\) and \(Q_{load,i}\) are reactive power inject into node \(i\), superior grid inject reactive power, wind power inject reactive power, photovoltaic power inject reactive power and reactive load value;

2) Inequality constraints

\[I_{y,\text{min}} \leq I_y \leq I_{y,\text{max}}\]  

(6)

Where: \(I_{y,\text{max}}\), \(I_{y,\text{min}}\) are the maximum and minimum current of branch \(ij\); \(I_y\) represents the current of branch \(ij\).

\[U_{i,\text{min}} \leq U_i \leq U_{i,\text{max}}\]  

(7)

Where: \(U_{i,\text{min}}\), \(U_{i,\text{max}}\) are the maximum and minimum voltage of node \(i\); \(U_i\) represents the voltage of node \(i\).

\[Q_{DG,i,\text{min}} \leq Q_{DG,i} \leq Q_{DG,i,\text{max}}\]  

(8)

Where: \(Q_{DG,i,\text{min}}\), \(Q_{DG,i,\text{max}}\) are the maximum and minimum reactive power of DG; \(Q_{DG,i}\) represents the reactive power of DG.

\[\Delta P_{i,\text{cut}} \leq P_{i,\text{cut}} \times 15\%\]  

(9)

Where: \(\Delta P_{i,\text{cut}}\) represents the user \(i\) load reduction; \(P_{i,\text{cut}}\) represents the user \(i\) load value.

\[0.95 \times p.u \leq U_{oltc} \leq 1.05 \times p.u\]  

(10)

Where: \(U_{oltc}\) represents the voltage of on-load voltage regulating transformer.

3. Joint optimization of active and reactive power in active distribution network based on ISA-MOPSO algorithm

3.1. Algorithm principle

In order to improve the shortcomings of the Multi-objective Particle Swarm Optimization (MOPSO), such as poor convergence and easy to fall into local optimization. In this paper, based on the MOPSO algorithm, the cross mutation operation in the genetic algorithm is introduced to optimize the particles, and the Metropolis criterion in the simulated annealing algorithm is used to select the updated particles to form an improved simulated annealing multi-objective particle swarm algorithm (ISA-MOPSO).

3.2. Algorithm improvement

The crossover operation of genetic algorithm is introduced into the MOPSO algorithm, and all particles are sorted according to the fitness of each generation of calculation results. Half of the particles with good fitness can directly enter the next generation, and a certain number of particles are selected in the other half according to the crossover probability, then replacing and recombining parts of the structure.
of the positions and velocities of these particles to obtain new positions and velocities. The position and speed substitution formula is as follows:

1) Cross operation

\[
\begin{align*}
    x'_1 &= D \times x_1 + (1-D) \times x_2 \\
    x'_2 &= D \times x_2 + (1-D) \times x_1
\end{align*}
\]

(11)

Where: \( x_1, \ x_2 \) are the particle position before crossover; \( x'_1, \ x'_2 \) are the particle position after crossover; \( D \) is a vector whose dimension is the number of particles to be crossed, and each component takes a random value between 0 and 1.

\[
\begin{align*}
    v'_1 &= D \times v_1 + (1-D) \times v_2 \\
    v'_2 &= D \times v_2 + (1-D) \times v_1
\end{align*}
\]

(12)

Where: \( v_1, \ v_2 \) are the particle velocity before crossover; \( v'_1, \ v'_2 \) are the particle velocity after crossover.

2) Metropolis criteria for screening particles after crossing

In this section calculates the fitness value of the updated particle, compares the fitness value before and after the update, and filters through the Metropolis criterion to remove the particle whose updated position is inferior to the previous. The screening process is as follows:

\[
\begin{align*}
    &\text{If } \min \left(1, \exp \left( \frac{f(x'_i) - f(x_i)}{T_k} \right) \right) > \text{rand}, \ x_i \text{ is replaced by } x'_i, \ \text{otherwise } x_i \text{ remains unchanged; } T_k \text{ is the current annealing temperature; } k \text{ is the current number of iterations.}
    \\
    \end{align*}
\]

3) Mutation operation

The mutation operation can enhance the local search ability of the algorithm, accelerate the particle to converge to the optimal solution, and raise its ability to jump out of the local optimal. The mutation operation selects a part of the particles according to the mutation probability, and then mutates the particles according to the Gaussian mutation formula. The particle mutation formula is shown below:

\[
    x'_i = x_i \times (1 + \text{Gaussian}(\sigma))
\]

(13)

Where: \( x'_i \) represents particle position after mutation; \( \text{Gaussian}(\sigma) \) is the normal random distribution from 0 to 1.

4) Metropolis criteria for screening particles after mutation

The operation in this section is similar to the operation after the cross operation. If

\[
\min \left(1, \exp \left( \frac{f(x'_i) - f(x_i)}{T} \right) \right) > \text{rand}, \ x_i \text{ is replaced by } x'_i, \ \text{otherwise } x_i \text{ remains unchanged.}
\]

3.3. Model solving process

In this paper, the ISA-MOPSO algorithm is used to solve the multi-objective problem of active and reactive power joint optimization in active distribution network. The flow chart is shown below.
4. Example simulation
In this paper, the joint optimization of active and reactive power adopts the method of regional optimization. The tie switch as a boundary divides the distribution network into several optimized sub-regions, if a voltage deviation occurs in the sub-region, the scheduling resources in this sub-region are adjusted first, and if the dispatch resources in the sub-area cannot meet the requirements of the safe operation of the distribution network, the global dispatch optimization of the distribution network is performed.

4.1. Parameters
In the calculation example, the distribution network structure adopts the standard IEEE33 node structure. The wind power, photovoltaic access points and distribution network partitions are shown in Figure 2; wind power output and photovoltaic power output are shown in Figure 3; the load reduction price of users who participate in direct load control is shown in Figure 4; industrial load data is shown in Figure 5; commercial and residential load data are shown in Figure 6; all kinds of load access points is shown in Table 1; the step size of the on-load voltage regulating transformer is 0.025; the system reference power is 10MVA; the voltage reference value is 12.66kV and the node voltage operating constraints range from 0.93 to 1.07p.u. The Industrial load does not participate in load reduction and control variables are load reduction, DG reactive power output and transformer tap position.
Figure 2. Adjusted IEEE33 node.

Figure 3. Wind power and photovoltaic power output data.

Figure 4. Participate in direct load control user bidding.

Figure 5. Industrial load data.

Figure 6. Resident and business load data.

Table 1. All kinds of load access points.

| Load type          | Access node |
|--------------------|-------------|
| Industrial load    | 19,20,23,24 |
| Business load      | 9,12,27,29,30,31 |
| Resident load      | 4,11,13,15,26,28 |
4.2. Analysis of Optimization scheme

According to calculating the voltage of each node throughout the day, it is found that node 9, node 10, node 11 and node 12 at 11:00 and node 9, node 10, node 11, node 12 and node 13 at 19:45 have large voltage deviations. The joint optimization of active and reactive power is used in the area where these nodes are located and the optimal solution group under this optimization is a series of particles closest to the origin of coordinates. The optimization results is shown below.

| Scheme | Load reduction cost/CNY | PV2 reactive power output/MW | Active loss/MW | Load reduction/MWH |
|--------|-------------------------|-------------------------------|---------------|-------------------|
|        |                         |                               |               | Node 9           |
| 1      | 159.23                  | 1.022                         | 2.016         | 0.094            |
| 2      | 168.85                  | 1.409                         | 1.993         | 0.33             |
| 3      | 188.49                  | 0.832                         | 1.985         | 0.057            |
| Not optimized | 0                  | 2.626                         | 2.683         | 0                |

The optimization results are shown in the following figures:

- Figure 7. Optimization Results at 11:00.
- Figure 8. Optimized voltage at 11:00.
- Figure 9. Optimization Results at 19:45.
- Figure 10. Optimized voltage at 19:45.
Table 3. Optimization results of each scheme at 19:45.

| Scheme | Load reduction cost/CNY | PV2 reactive power output/MW | Active loss/MW | Load reduction/MWH |
|--------|-------------------------|-----------------------------|----------------|-------------------|
| 1      | 291.47                  | 6.956                       | 2.929          | 0.099 1.04 0.061 0.032 0.023 |
| 2      | 294.41                  | 7.652                       | 2.882          | 0.104 0.085 0.045 0.038 0.052 |
| 3      | 297.04                  | 7.803                       | 2.867          | 0.104 0.104 0.076 0.030 0.008 |
| Not optimized | 0                  | 7.803                       | 3.582          | 0 0 0 0 0 |

Figure 8 and figure 10 show that the voltage value in each scheme has been significantly improved and the voltage value at each node is within the range required for safe operation. Table 2 and table 3 show that the active loss in each scheme has been greatly reduced after optimization.

In conclusion, the load reduction generates a certain amount of control costs, but it obtains more considerable economic benefits, the active and reactive joint optimization can quickly restore the distribution network operating state to the safe range, balance the distribution of power flows and reduce network losses. There are a variety of optimization options to choose from, it increases the flexibility of distribution network optimization scheduling.

5. Conclusion

In order to meet the large-scale access of renewable energy to the distribution network and improve the safety and stability of the power grid operation, this paper establishes the active and reactive power joint optimization model to solve the power grid operation problems caused by the randomness of new energy output. Compared with traditional optimized scheduling, the joint active and reactive power optimization in this paper is more flexible and superior, it can not only ensure the safe and stable operation of the distribution network, but also enhances the grid's capability to accept renewable energy, which meets the needs of actual power grid operation.

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