A novel reactive power optimization method for distributed power system using PSO

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Abstract. In order to solve the problem of coordinated optimization of capacitor banks and distributed power sources under load fluctuation conditions, a new dynamic reactive power optimization method for distribution networks is proposed. Firstly, a stochastic model of distributed power supply and load is established. The Monte Carlo simulation sampling is used to obtain the distributed power output curve and load curve of 24 h. And the random power flow analysis method based on semi-invariant method is studied. Secondly, the distributed power investment benefit and network active loss are the objective functions, and the multi-objective dynamic reactive power optimization model of active distribution network is established. Then, based on the adaptive particle swarm optimization (PSO) algorithm, the solution method and process of the model are proposed. At last the validity and practicability of the proposed method are verified.

1. Introduction
As an important means of economic operation of distribution network, reactive power optimization of distribution network has been paid increasing attention. Reasonable reactive power distribution can effectively reduce system loss and improve voltage quality. On the one hand, since the actual medium load changes continuously with time, the control equipment should be adjusted in real time to meet the needs of the system operation. On the other hand, the limitation of the number of times of controlling the operation of the equipment should be considered, which makes the problem more complicated [1].

The proportion of distributed generation DG (distributed generation) in the distribution network is gradually increasing, and DGs can effectively improve the shortage of reactive power in the distribution network [2]. However, the coordinated control of DG and traditional reactive devices also poses new challenges for reactive power optimization in distribution networks [3-4]. Therefore, studying the dynamic reactive power optimization problem of distribution network with DG has important practical and theoretical value for improving distributed power efficiency and reducing network transmission loss.

For the reactive power optimization problem of capacitor banks and distributed power sources under load fluctuation conditions, [5] constructed a dynamic reactive power optimization model, but did not consider the access problem of DG. With DGs, reactive power optimization mathematical model and system Reactive power regulation and control methods will change; in [6], based on static reactive power optimization of distribution network, a reactive power optimization strategy for capacitor banks and distributed power supplies is proposed, but the actual load and distributed power output are changes. Considering dynamic reactive power optimization is more practical; [7] increases
the capacitor investment cost and node voltage offset as the objective function based on the traditional reactive power optimization, making the control more flexible, but not considered in the optimization target. In the reactive power optimization algorithm, the artificial intelligence algorithm has been widely studied and applied in the reactive power optimization problem, which effectively improves the accuracy of the solution. Other applications of PSO include Antenna [8], Electromagnetics [9] etc.

This paper is based on adaptive particle swarm optimization (APSO) algorithm, multi-objective dynamic reactive power optimization for DG-containing distribution networks, and established a reactive power optimization model to solve the capacitor bank under load fluctuation conditions. By comparing with genetic algorithm GA (genetic algorithm) and traditional particle swarm optimization PSO (particle swarm optimization) algorithm, the proposed global search performance and solution accuracy are verified. Finally, the rationality and effectiveness of the proposed algorithm are verified by reactive power optimization.

2. Adaptive particle swarm optimization based on distributed entropy

2.1. Processing of decision variables
The decision variables of reactive power optimization in distribution network include continuous variables and discrete variables. The discrete variables in this paper are the switching capacity of reactive power compensation equipment, and the continuous variable is the reactive power output of distributed power. That is, the reactive power optimization of distribution network is a mixed integer. In this paper, the method of joint coding of integer and real numbers is adopted, in which the integer represents the discrete variable, that is, the number of switching groups of the reactive power compensation device, and the real number represents the continuous variable, that is, the reactive power output of the distributed power source. The specific composition of discrete variables is expressed as

$$ C = \begin{bmatrix} C_{1,1} & C_{1,2} & \ldots & C_{1,24} \\ C_{2,1} & C_{2,2} & \ldots & C_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ C_{N,1} & C_{N,2} & \ldots & C_{N,24} \end{bmatrix} $$

$$ T_i = [0 \ t_{i,1} \ t_{i,2} \ \ldots \ \ t_{i,n_{c_{max}}} ] $$

Where: C is the capacitor switching capacity matrix, the elements in the matrix are integers; CN, 24 is the switching capacity of capacitor N in the 24th period; T_i is the pre-preparation of capacitor i according to the previous n_{c_{max}} capacitors variation value. The specific composition of the continuous variable is expressed as

$$ X_{DG} = \begin{bmatrix} P_{DG_{i,1}} \ P_{DG_{i,2}} \ \ldots \ \ P_{DG_{i,24}} \\ Q_{DG_{i,1}} \ Q_{DG_{i,2}} \ \ldots \ \ Q_{DG_{i,24}} \\ P_{DG_{N,1}} \ P_{DG_{N,2}} \ \ldots \ \ P_{DG_{N,24}} \\ Q_{DG_{N,1}} \ Q_{DG_{N,2}} \ \ldots \ \ Q_{DG_{N,24}} \end{bmatrix} $$

Where: X_{DG} is the set of active and reactive power of distributed power supply, the elements in the matrix are real numbers; P_{DG_{i,l}}, Q_{DG_{i,l}} are the active and reactive power of distributed power supply N at time i.

2.2. Improved adaptive particle swarm optimization algorithm
The main control parameters of the standard particle swarm optimization algorithm are inertia weight and learning factor [5]. Since the learning factor adopts a fixed value, the inertia weight is adjusted too linearly with the linearly decreasing update strategy, resulting in slow algorithm optimization and low accuracy [7]. The adaptive inertia weight update strategy based on distributed entropy balances the global and local search performance of the algorithm and improves the algorithm search accuracy. The design steps are as follows.
Step 1 During each iteration of the PSO algorithm, calculate the maximum diagonal distance between the population particles as

\[ L(t) = \max \| x_i(t), x_j(t) \|_2 \]  

Where, the direction vector between the two particles \( x_i(t) \) and \( x_j(t) \) is \( g(t) \).

Step 2 Calculate the projection of each particle on the vector \( g(t) \) to get the set \( y(t) \), given as

\[ y(t) = g(t)^T x(t) \]  

Step 3 Divide \( g(t) \) by the population size \( \text{popN} \), and count the number of particle projections for each interval segment, denoted as \( h_i(t) \).

Step 4 Calculate the population distribution entropy \( E(t) \) for each iteration.

\[ s_i(t) = h_i(t)/N \]  

\[ E(t) = -\sum_{i=1}^{N_{\text{max}}} s_i(t) \ln s_i(t) \]  

Step 5 Calculate the inertia weight \( \omega(E(t)) \) obtained from each iteration according to Equation (7).

\[ \omega(E(t)) = 1/(1 + 1.5e^{-2.6E(t)}) \]  

Distribution entropy is the degree of dispersion that describes the distribution of particles in the search space. In the early stage of algorithm search, the particle swarm distribution is wide. At this time, the distribution entropy is large (\( \omega \) is large), which is beneficial to improve the global search performance. In the later stage of the algorithm search, the particle distribution is dense, and the smaller distribution entropy (\( \omega \) is smaller), which can enhance local development capabilities. From the above analysis, the algorithm can dynamically adjust \( \omega \) by distributing entropy to the current population environment information, and balance the global and local search capabilities. In the iterative process of the algorithm, the learning factor plays a role in guiding the particle speed update. The learning factor is used to update the strategy asynchronously, so that the learning factor adapts to the change of the population congestion degree and searches for the optimal solution. Update policy is

\[ c_1 = c_{1,\text{ini}} + \frac{c_{1,\text{fin}} - c_{1,\text{ini}}}{N_{\text{max}}} n \]  

\[ c_2 = c_{2,\text{ini}} + \frac{c_{2,\text{fin}} - c_{2,\text{ini}}}{N_{\text{max}}} n \]  

where \( n \) and \( N_{\text{max}} \) are the number of iterations and the maximum number of iterations; \( c_{1,\text{ini}}, c_{2,\text{ini}} \) and \( c_{1,\text{fin}}, c_{2,\text{fin}} \) are the initial and final values of the learning factors \( c_1 \) and \( c_2 \), respectively.

2.3. Reactive power optimization module with embedded random current

Taking the adaptive particle swarm optimization algorithm as the main body, the stochastic power flow is embedded in the algorithm optimization process. Figure 1 shows the adaptive particle swarm optimization algorithm for solving reactive power optimization.

2.4. Capacitor switching timing is determined

Since the DG output has fluctuations and the load changes are random, when the DG and the load change, the switching capacity of the capacitor bank also changes, so that the capacitor bank is frequently switched. In dynamic reactive power optimization, the number of switching of the capacitor bank is limited, so that the capacitor bank operates within a normal switching range. In this paper, according to the pre-action table method, the switching timing and switching capacity of the capacitor bank are determined, so that the capacitor bank meets the requirements of the number of switching. Firstly, the static reactive power optimization calculation result of each time period is used to determine the reactive power compensation value of the capacitor, thereby distributing the action authority of the capacitor group.

\[ S_{C_{i,t}} = 1 \]  

means that the capacitor bank operates at time \( t \), and vice versa. Firstly, according to the static reactive power optimization result, the capacitor switching capacity change is calculated: \( \Delta C_{i,t} = C_{i,t} - C_{i,t-1} \), \( C_{i,t} \) and \( C_{i,t-1} \) respectively represent capacitor group \( i \) at \( t \) and \( t-1 \). The number of groups is input in a period of time, and the initial time \( C_{i,1} \) is defined as \( \Delta C_{i,1} = C_{i,1} - C_{i,24} \). Sort \( \Delta C_{i,t} \),
assign action rights according to the size of $\Delta C_{Lt}$, when $\Delta C_{Lt}$ is the same and the number of actions is not enough, then $\Delta C_{Lt-1} + \Delta C_{Lt} + \Delta C_{Lt+1}$ instead of $\Delta C_{Lt}$ to assign action permissions.

It is assumed that the capacitor group is allowed to operate at time $t$, the static reactive power optimization calculation is performed again, the capacitor group variation difference at the subsequent time is recalculated, and the action time is re-allocated. This assignment does not affect the capacitor switching authority and capacity made in the previous moment, and thus the time and compensation capacity of the capacitor bank operation are obtained five times.

3. Case analysis

3.1. Case study
In this paper, the IEEE-30 node power distribution system is used for reactive power optimization calculation. The distributed power supply of the access system, including WT, PV power station and FC, is connected to the distribution network by constant power factor control. The access position is shown in Figure 2. PV1 is connected to node No. 5 and PV2 is connected to node No. 23. The rated capacity is 400 kW, which is treated as a negative PQ node in the power flow calculation process. The capacitor bank of the access system is represented by CB. It is CB1 for accessing node No. 3 and CB2 for accessing node No. 26. The installation capacity is 300 kvar, and the single-group capacity is 10 kvar.

**Figure 1.** Reactive power optimization algorithm based on embedded random power flow.

[Diagram of the algorithm]

Input capacitor and distribution network data, initialization algorithm parameters

Randomly generate the velocity and position of $N$ particles

Calculate the network loss and voltage value of each particle optimization scheme by applying random power flow

Update inertia weight and learning factor according to equations (26)–(30)

Particle position and speed update

The random power flow calculation obtains the evaluation index of the particle optimization scheme, and updates the optimal position of the particle $P_g$.

If $n < N_{max}$

Yes

No

Output optimization results

$n = n + 1$
kvar, which is the largest in one day. The number of cuts was 5 times. The 24 h load situation of the system is shown in Figure 3. The 24 h wind speed and PV output curve are shown in [9].

![30-node power distribution system](image)

**Figure 2.** 30-node power distribution system.

![Load distribution in 24 hours](image)

**Figure 3.** Load distribution in 24 hours.

3.2. **Optimization results analysis**

Algorithm parameter setting: population size is 80; iteration number is 100; learning factor $C_1 = C_2 = 2$; the inertia weight of PSO algorithm decreases linearly from 0.9 to 0.4 with the number of iterations; APSO algorithm dynamically adjusts inertia according to the current entropy-aware population current search environment information Weight update; GA’s crossover operator and mutation operator are 0.8 and 0.25, respectively.

Based on the three algorithms, the reactive power optimization calculation of the distribution network with distributed power supply is carried out separately. Figure 4 shows the convergence curves of each optimization algorithm. It can be seen from Figure 4 that the PSO algorithm lacks the
feedback of the population search information, the global search ability is weak, and the accuracy of the algorithm is not high. Because the current population search environment information is transmitted to the inertia weight through the distributed entropy, and the inertia weight is guided to update reasonably. The APSO algorithm has strong global search capability, has high global search performance, and reduces the possibility that the algorithm falls into local optimum. The search ability of the GA algorithm is better than the PSO algorithm, but still not as good as the APSO algorithm.

4. Conclusion
Dynamic reactive power optimization of distribution network is an effective means to reduce network loss, optimize operation and improve economic efficiency, and is widely used in actual operation. Based on the adaptive particle swarm optimization algorithm, a multi-objective dynamic reactive
power optimization model for distribution network with DG is established, and the multi-objective dynamic reactive power optimization results of the model are solved. The adaptive particle swarm optimization algorithm is compared with genetic algorithm and traditional particle swarm optimization. The fast convergence of the algorithm solves the problem of coordinated optimization of capacitor banks and distributed power supplies under load fluctuation conditions. The results of the example show that compared with the previous reactive power network optimization, the proposed multi-objective dynamic reactive power optimization model of the distribution network is more in line with the actual situation. The satisfaction of the adaptive particle swarm optimization algorithm is best.

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