Multi-objective Reactive Power Optimization Based on Improved Particle Swarm Algorithm

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Abstract. In this paper, an optimization model with the minimum active power loss and minimum voltage deviation of node and maximum static voltage stability margin as the optimization objective is proposed for the reactive power optimization problems. By defining the index value of reactive power compensation, the optimal reactive power compensation node was selected. The particle swarm optimization algorithm was improved, and the selection pool of global optimal and the global optimal of probability (p-gbest) were introduced. A set of Pareto optimal solution sets is obtained by this algorithm. And by calculating the fuzzy membership value of the pareto optimal solution sets, individuals with the smallest fuzzy membership value were selected as the final optimization results. The above improved algorithm is used to optimize the reactive power of IEEE14 standard node system. Through the comparison and analysis of the results, it has been proven that the optimization effect of this algorithm was very good.

1. Introduction

With the continuous development of industrial level and technology, the demand for power quality of people has got higher and higher, and the power transmission loss has been expected to be as small as possible. In order to improve power quality, reduce network loss and improve voltage stability, it's essential to optimize reactive power of the power system and make full use of reactive power supply.

It is needed to establish the reactive power optimization model and set objective function when reactive power of the power system is optimized. In the initial stage of reactive power optimization, only the active power loss is considered as an objective function. With the development of theoretical study, reactive power optimization has gradually become a multi-objective optimization problem with comprehensive consideration of active power loss, voltage level and voltage stability margin [1, 2]. When dealing with multi-objective optimization problems, the most common way is to simplify the processing of multiple targets, such as weighted method [3], ε-dominance method [4], membership degree method [6], etc. This approach makes the optimization path constrained, and has a lot of human factors in determining the weight of each target, so it is difficult to find the optimal solution. Based on the idea of sorting the non-inferior optimal solution [6], the space for multi-objective optimization is
expanded, and the conflicting problems of each target are well handled, and the compromise between multiple targets is realized. Therefore, it is more and more widely applied to multi-objective optimization problems. Based on the method of sorting the non-inferior optimal solution, a set of Pareto optimal solution set is obtained by multi-objective optimization. In practical application, it is often necessary to select an optimal solution from this set of Pareto optimal solution set. For this reason, this set of Pareto optimal solution set needs to be filtered. The fuzzy membership function can be used to measure the proximity of these Pareto optimal solutions and ideal solutions conveniently and succinctly, so as to provide the basis for the selection of Pareto optimal solution.

At present, reactive power optimization adopts the method of selecting fixed nodes to compensate reactive power, which lacks comprehensive judgment. In this paper, the reactive power compensation node is selected by defining the index value of power compensation, which makes the selection of reactive power compensation node more scientific and reasonable, and greatly improves the effect of reactive power optimization.

The development of computer technology makes the automation of all aspects of society continue to improve, the demand for optimization algorithm is increasing, and a variety of optimization algorithms have been proposed, such as: genetic algorithm[7], particle swarm optimization[8-13], ant colony optimization[14]. Particle swarm optimization (PSO), as a swarm intelligence algorithm, has the characteristics of fast convergence, simple and easy programming. It is widely used in optimization problems. However, due to the optimization mechanism of PSO, premature phenomenon can occur. The particle swarm optimization is improved in this paper, and the selection pool of global optimal and global optimal of probability (p-gbest) are proposed. Therefore, the local optimization ability of the algorithm is improved and the possibility of premature occurrence is reduced.

2. Reactive power optimization model of power system

2.1. Reactive power optimization objective function

The objective function model of reactive power optimization proposed in this paper is as follows:

\[
\begin{align*}
& f_1 = \min(P_{sw}) = \\
& \quad \sum_{K=i}^{N} G_k(i, j) \left[ U_i^2 + U_j^2 - 2U_i U_j \cos \theta_{ij} \right] \\
& f_2 = \min(\Delta U) = \sum_{i} \left[ \frac{U_i - U_i^{spec}}{\Delta U_i^{max}} \right]^2 \\
& f_3 = \max(V_{sw}) = \delta_{min}
\end{align*}
\]

Where , \( P_{sw} \) is the active network loss of the system, and \( N_i \) is the branch set; \( G_k(i, j) \) is the conductance of the branch \( K \); \( \theta_{ij} \) is the voltage phase angle difference between node \( i \) and node \( j \); \( \Delta U \) is the voltage deviation; \( N_L \) is the load node set; \( U_i \) is the actual voltage of the node; and \( U_i^{spec} \) is the expected voltage value of the node, \( \Delta U_i^{max} \) is the upper limit of node voltage deviation, \( \Delta U_i^{max} = U_i^{max} - U_i^{min} \); \( V_{sw} \) is the static voltage stability margin; and \( \delta_{min} \) is the minimum singular value of the Jacobi matrix in Newton Raphson method.

2.2. Equation of equality constraint

The power constraint equation of the system is as follows:

\[
\begin{align*}
& P_G - P_D - U_i \sum_{j \in N} U_j \left( G_{i,j} \cos \theta_{ij} + B_{i,j} \sin \theta_{ij} \right) = 0 \\
& Q_G + Q_D - Q_{i} = U_i \sum_{j \in N} U_j \left( G_{i,j} \sin \theta_{ij} - B_{i,j} \cos \theta_{ij} \right) = 0
\end{align*}
\]
Where \( i \in N_{PQ}, N_{PQ} \) is a set of PQ nodes; \( P_{Gi} \) is the active output power of the generator node and \( P_{PQ} \) is the active power absorbed by the load node; \( Q_{Gi} \) is the reactive output power of the generator node, \( Q_{PQ} \) is the reactive power absorbed by load nodes, \( Q_{Di} \) is the reactive power compensated by compensation nodes; \( G_{ij} \) is the conductance between node \( i \) and node \( j \); \( B_{ij} \) is the electrical susceptance between node \( i \) and node \( j \); \( N \) is the total number of the nodes in the system.

### 2.3. Equation of inequality constraint

The variables of the reactive power optimization model must not exceed the specified range. The variables are divided into control variable and state variable. Control variable include generator terminal voltage \( U_{Gi} \), compensation capacitance of compensating capacitor \( C_{j} \), transformer ratio \( T_{k} \).

\[
\begin{align*}
U_{Gi_{\min}} & \leq U_{Gi} \leq U_{Gi_{\max}}, \quad i \in N_{G} \\
C_{j_{\min}} & \leq C_{j} \leq C_{j_{\max}}, \quad j \in N_{C} \\
T_{k_{\min}} & \leq T_{k} \leq T_{k_{\max}}, \quad k \in N_{T}
\end{align*}
\]  
(3)

Where \( U_{Gi_{\max}} \) and \( U_{Gi_{\min}} \) are the upper and lower limits of the generator terminal voltage; \( C_{j_{\max}} \) and \( C_{j_{\min}} \) are the upper and lower limits of the compensation capacity of the capacitor; \( T_{k_{\max}} \) and \( T_{k_{\min}} \) are the maximum and minimum values of the transformer ratio; \( N_{G} \) is the number of nodes in the generator, \( N_{C} \) is the number of nodes of the compensating capacitor, and \( N_{T} \) is the branch number of transformer.

The node voltage \( U_{l} \) of each load and the reactive output power \( Q_{Gi} \) of the generator are the state variables. The constraint equations of the state variables are as follows:

\[
\begin{align*}
Q_{Gi_{\min}} & \leq Q_{Gi} \leq Q_{Gi_{\max}}, \quad i \in N_{G} \\
U_{l_{\min}} & \leq U_{l} \leq U_{l_{\max}}, \quad l \in N_{PQ}
\end{align*}
\]  
(4)

Where \( Q_{Gi_{\max}} \) and \( Q_{Gi_{\min}} \) are the upper and lower limits of the reactive output power of the generator; \( U_{l_{\max}} \) and \( U_{l_{\min}} \) are the upper and lower limits of the voltage of the load nodes.

### 3. Selection of compensation capacitor node

At present, when dealing with the problem of reactive power optimization, the fixed nodes are selected to compensate for the reactive power of the standard node system. This method lacks of comprehensive judgment and leads to poor compensation. In this paper, through the comprehensive evaluation of reactive power compensation nodes, the optimal reactive power compensation node is selected to make the reactive power optimization more reasonable and effective.

In order to determine the optimal reactive power compensation nodes, the urgency of reactive power compensation of each compensation node is ordered. The sequencing mainly considers the voltage stability of the node itself and the influence of the reactive power injected from the node on the voltage level of the whole power system.

In order to measure the voltage level, the voltage stability margin \( \xi \) of the nodes must be determined first, and the voltage level of the nodes is related to the load in the area. The relationship between load voltage and regional load is shown in figure 1. With the increase of regional load, the voltage level of the nodes drops and the system is in stable state before the voltage collapse point is reached.
When the load continues to increase, the voltage collapses, and the system is in a state of unstable operation. The calculation formula of voltage stability margin $\xi$ is shown in (5):

$$\xi = \frac{P_{\text{max}} - P_0}{P_0}$$  \hspace{1cm} (5)

Where $P_0$ is the load power at the node area for normal operation, and $P_{\text{max}}$ is the maximum load power at the node area before the system collapse. The voltage stability margin $\xi$ is used to measure the voltage stability level of the nodes.

The reactive power injected from nodes will affect the voltage level of the whole power system, this effect is mainly manifested in the influence of the voltage level of each node. When the node $i$ is injected with reactive power, the voltage level of the node $j$ will be affected, and these effects include: $\frac{\partial U_j}{\partial Q_i}$, which is the sensitivity reflecting the relationship between the change of the voltage of node $j$ and the reactive power injected from node $i$ and $\xi_j$, which is the voltage stability margin of node $j$ after node $i$ is injected with the reactive power. In this paper, the two factors are combined to measure the index value of the effect of reactive power injected from node $i$ on the voltage of node $j$, and the index value is set to be $R_{ij}$, whose definition is shown in (6):

$$R_{ij} = \frac{\partial U_j}{\partial Q_i} \times \frac{1}{\xi_j}$$  \hspace{1cm} (6)

The index value of the influence degree of node $i$ on the voltage level of the whole power system is set to be $R_i$, whose definition is shown in (7):
Sorting each node according to the urgency of reactive power compensation, it is necessary to define the index value of reactive power compensation of node, as shown in (8):

\[ S_i = R_i \times \frac{1}{\xi_i} \]  

Where \( S_i \) is the index value of reactive power compensation of the node \( i \); \( R_i \) is the index value of the degree of the influence of the node \( i \) on voltage level of power system; \( \xi_i \) is the voltage stability margin of the node itself. The larger the \( R_i \), the greater the influence of node \( i \) on the voltage level of the whole power system; the smaller the \( \xi_i \), the worse the voltage stability of node \( i \) itself and the larger the index value of reactive power compensation \( S_i \) of node \( i \), which means the greater the urgency degree of reactive power compensation for node \( i \). All nodes in the standard node system are calculated and sorted according to the formula (5) ~ (8). Therefore, the optimal reactive power compensation node in the system can be determined, and it makes the selection of optimal reactive compensation node is more reasonable and effective.

4. Improvement and Optimization of Particle Swarm Optimization

4.1. Standard Particle Swarm Optimization

The particle swarm optimization algorithm is an intelligent algorithm based on group iterative optimization. Each particle updates its optimization speed and the position of the solution space according to the selected global optimal position and individual optimal position. The formula is as follows:

\[ v_{id}^{(t+1)} = w_{id} v_{id}^{(t)} + c_1 r_1 (p_{id}^{(t)} - x_{id}^{(t)}) + c_2 r_2 (p_{gdd}^{(t)} - x_{id}^{(t)}) \]  

\[ x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)} \]  

Where \( d = 1,2,..n \), \( n \) is the dimension of the variable and is equal to the number of control variables of the optimized objective function; \( i = 1,2,..M \), \( M \) is the population size; \( t \) is the current evolutionary algebra; \( r_1 \) and \( r_2 \) are the random numbers uniformly distributed over [0,1]; \( c_1 \) and \( c_2 \) are the acceleration constants; \( w \) is the inertia weight; \( v_{id} \) is the \( d \)th component of the velocity vector of the \( i \)th particle; \( p_{id} \) is the \( d \)th component of the individual optimal position of the \( i \)th particle; \( p_{gdd} \) is the \( d \)th component of the group optimal position vector; \( x_{id} \) is the \( d \)th component of the position vector of the \( i \)th particle.

4.2. Improvement of Particle Swarm Optimization Algorithm

The optimization mechanism of the particle swarm algorithm leads to the fact that the local optimal solution is often obtained. By introducing the selection pool of global optimal and the global optimal of probabilistic (p-gbest), the possibility of premature phenomena in particle swarm optimization is greatly reduced. The selection pool of global optimal selects the partial particles in the external archives as the global optimal position to achieve the purpose of fine tuning, and p-gbest can maintain the diversity of the particle group and enhance the local search ability of the algorithm.
4.2.1. Global Optimal Selection Pool. Each particle chooses a different global optimal value (gbest) in the selection pool, so that the optimized non-inferior solution tends to be homogenized. The specific process is as follows:

1) According to the size of the niche fitness value to set the probability that the non-inferior solution is selected in the external archives, and then putting them into the selection pool, through repeated tests, setting the pool size \( N_{ls} = 5 \).

2) A non-inferior solution which is in the above selection pool is selected in a random way by all particles to be their own global optimal gbest.

4.2.2. Probability Global Optimization. The optimization mechanism of PSO makes it easy to get local optimal solutions, p-gbest can slow down the convergence rate of the PSO and reduce the possibility of falling into the local optimum. P-gbest converts a specific global optimal position to a possible range, the formula is as follows:

\[
p_{p_{gd}}^{(t)} = N(p_{gd}^{(t)}, \sigma), \sigma = f(t)
\]

\[
x_{ad}^{(t+1)} = w_{ad}^{(t)}x_{ad}^{(t)} + c_1r_1(p_{gd}^{(t)} - x_{ad}^{(t)}) + c_2r_2(p_{gd}^{(t)} - x_{ad}^{(t)})
\]

Where \( t \) is the number of iterations; \( p_{p_{gd}}^{(t)} \) is the dth component of the p-gbest and is the random variable of the normal distribution; \( p_{gd}^{(t)} \) is the dth dimensional component of gbest; \( \sigma \) is the uncertainty that describes gbest as the optimal value; \( f(t) \) is as shown in (13):

\[
f(t) = \begin{cases} 
\sigma_{\max}, & t < \alpha \cdot g_{\max} \\
\sigma_{\min}, & t \geq \alpha \cdot g_{\max}
\end{cases}
\]

Where \( g_{\max} \) is the maximum number of iterations; \( \sigma_{\max}, \sigma_{\min} \) and \( \alpha \) are appropriate to take 0.15, 0.0001 and 0.4 as their value respectively.

In the early stage of the iteration, the value of \( \sigma \) is larger, the p-gbest changes in a large range, and the global search ability is stronger; in the late stage of the iteration, \( \sigma \) is reduced, the p-gbest changes in a smaller range, and the local search ability is enhanced. Therefore, p-gbest can improve the defect of too fast convergence speed of PSO and reduce the possibility of local optimal solution.

4.3. Determination of the optimal solution

In this paper, the result of the multi-objective reactive power optimization algorithm is a set of praetor optimal solution sets, and in practical applications, it is needed to select an optimal solution from the praetor optimal solution set as the final optimization result. Therefore, it is needed to sort the praetor solution sets by assigning them and select the highest value of the non-inferior solution as the final optimization results.

Firstly, the three objective functions are transformed into fuzzy membership function, and the membership function is shown in (14) for the two minimum objective functions of network loss and node voltage deviation.

\[
\mu(f_j) = \begin{cases} 
0, & f_j \leq f_{j_{\min}} \\
f_j - f_{j_{\min}} & f_{j_{\min}} < f_j < f_{j_{\max}} \\
f_{j_{\max}} - f_{j_{\min}}, & f_j \geq f_{j_{\max}}
\end{cases}
\]
Where $f_j$ is the jth objective function, $j = 1, 2$, $f_{j_{min}}$ and $f_{j_{max}}$ are the minimum value and the maximum value of the jth objective function.

The voltage stability margin is the maximum objective function, its membership function is as shown in (15):

$$
\mu(f_j) = \begin{cases} 
0 & f_j \leq f_{j_{min}} \\
\frac{f_{j_{max}} - f_j}{f_{j_{max}} - f_{j_{min}}} & f_{j_{min}} < f_j < f_{j_{max}} \\
1 & f_j \geq f_{j_{max}}
\end{cases}
$$  

(15)

Where $j = 3$.

After constructing the membership function of each objective function, the membership value of each non-inferior solution in the pareto solution set can be calculated. The formula is shown in (16):

$$
\lambda_i = \frac{1}{n} \sum_{j=1}^{n} \mu(f_{ij})
$$  

(16)

Where $\lambda_i$ represents membership value of the ith non-inferior solution in the pareto solution set, $i = 1, 2, 3,...,10$; $f_{ij}$ represents the jth objective function of the ith non-inferior, $j = 1, 2, 3$; $n = 3$.

After determining the membership value of non-inferior solution, choosing the non-inferior solution with the minimum membership value in the pareto solution set as the final optimization result.

5. Multi-objective Reactive Power Optimization Based on Improved Particle Swarm Optimization

5.1. Basic definitions

Definition 1: If the control variables $x_1$ and $x_2$, are within the specified range, $x_1 \prec x_2$ can be used to describe that $x_1$ dominates $x_2$, if and only if:

$$
\begin{align*}
& f_i(x_1) \leq f_i(x_2), \forall i \in [1,...m] \\
& f_j(x_1) < f_j(x_2), \exists j \in [1,...m]
\end{align*}
$$

(17)

Where $m$ is the number of objective functions.

Definition 2: For any two control variables $x_i$ and $x_j$, $x_i$ dominants and constraints $x_j$, if and only if any of the following conditions holds:

1) $x_i$ is within the specified range, $x_i$ exceeds the specified range.
2) $x_i$ and $x_j$ both exceed the specified range, as for $x_i$, its extent of the restriction is smaller.
3) $x_i$ and $x_j$ are within the specified range, and $x_i \prec x_j$.

5.2 The deficiency of Multi-objective Reactive Power Optimization Based on Improved Particle Swarm Optimization

1) Set the parameters of the standard node system.
2) Calculate the index value of reactive power compensation of each node in the standard node system, and select the optimal reactive power compensation node.
3) Assign initial values to the particle group, and give the initial positions $x_0$ and initial velocities $v_0$ of particles in a random manner. The historical optimum position of the initial individual of a particle is $p_{best}=x_0$, the external archives is empty, the number of iterations $t = 0$;

4) Carry out the power flow calculation and obtain the objective function value. Sort the non-dominated solutions and construct the non-dominated solution set;

5) If there is a non-dominated solution to constraint and dominate the non-inferior solution in the external archives, or if there is no dominance relationship between the non-dominated solutions and the non-inferior solutions, save the non-dominated solution into an external archives and delete the dominated non-inferior solution.

6) Calculate the niche fitness of each particle [15-16]. According to the size of the niche fitness value to set the probability of the non-inferior solution was selected which is in the external file, and to select the non-inferior solutions to be put in the selection pool. Then the particle swarm selects a non-inferior solution in the selection pool as its global optimal solution in a random way.

7) According to (11), the p-gbest which is corresponding to the gbest is calculated. Obtain the velocity $v$ by using (12), and update the position $x$. Determine the constraint relationship and dominance relationship between the current position $x$ and the individual optimal position of the last iteration. Select the dominant one as the new individual optimal position.

8) If the number of the non-inferior solutions in the external archives is greater than the specified value, then remove the individuals with smaller value of niche fitness;

9) When the number of iterations reaches the given value, the optimization process is terminated, otherwise $t = t + 1$, and then turn to the step 4);

10) After performing the reactive power optimization, a set of non-inferior optimal solutions is obtained. The fuzzy membership value of each non-inferior optimal solution is calculated, and the non-inferior solution with the highest membership value is selected as the final optimization result.

6. Case Study
The specific parameters of the IEEE14 node system are shown in [17]. Population size is $M = 100$, the maximum permission iterative number is $g_{max} = 100$, $w = 0.729$, acceleration factor is $c_1 = c_2 = 1.494$, external file size is 100.

Firstly, the reactive power compensation of each load node in the IEEE14 standard node system is calculated. There are 5 generator nodes in this standard node system, and the remaining 9 are all load nodes. The index value of reactive power compensation for the 9 load nodes are calculated, and the results are shown in Table 1.

| Node | The index value of reactive power compensation /pu |
|------|----------------------------------|
| 4    | 0.993                            |
| 5    | 1.014                            |
| 7    | 1.275                            |
| 9    | 1.697                            |
| 10   | 1.789                            |
| 11   | 1.632                            |
| 12   | 1.006                            |
| 13   | 0.937                            |
| 14   | 1.208                            |

According to the table above, the node 10 is chosen as the reactive compensation node. The existing reactive compensation nodes are all fixed and node 9 is chosen. Reactive compensation is carried out for two nodes respectively, and the comparison of compensation effects is shown in table 2.

Table 1. Reactive power compensation index value of load node in IEEE14 node system
Table 2. Compensation effect of different compensation nodes

| Compensation method                              | 7    | 9    | 10   | 11   | 14   |
|-------------------------------------------------|------|------|------|------|------|
| Stability margin before compensation            | 0.461| 0.398| 0.286| 0.364| 0.428|
| Stability margin after the compensation for node 9| 0.482| 0.585| 0.468| 0.443| 0.498|
| Stability margin after the compensation for node 10| 0.463| 0.547| 0.576| 0.518| 0.541|

After reactive compensation is carried out for two different nodes, compare the data of the stability margin of the weak nodes in the IEEE14 standard node system showed in the above table, it can be seen that the stability margin of each weak node is higher when reactive power compensation is performed at node 10 instead of node 9. It shows that selecting the reactive power compensation node by calculating the index value of reactive power compensation of each load node is correct and effective. Finally, node 10 is chosen as the reactive power compensation node in this paper.

The reactive power optimization method proposed in this paper is used to obtain the distribution of the Pareto optimal solution in the external archive, as shown in figure 2.

Fig. 2 Spatial distribution of Pareto 10 non-inferior solutions with the greatest niche fitness are selected, as shown in Table 3.
Table 3. Pareto values of objective function of reactive power optimization

| Numble | Loss of network/pu | Voltage deviation /pu | Static voltage stability margin/ pu | Fuzzy membership value /pu |
|--------|--------------------|-----------------------|-----------------------------------|---------------------------|
| 1      | 0.1335             | 1.3446                | 0.5514                            | 0.4997                    |
| 2      | 0.1439             | 0.0613                | 0.5163                            | 0.4470                    |
| 3      | 0.1556             | 0.19271               | 0.5787                            | 0.3980                    |
| 4      | 0.1349             | 1.0371                | 0.5526                            | 0.4428                    |
| 5      | 0.1354             | 0.3935                | 0.5378                            | 0.3550                    |
| 6      | 0.1359             | 0.7642                | 0.5495                            | 0.4040                    |
| 7      | 0.1372             | 0.5017                | 0.5456                            | 0.3728                    |
| 8      | 0.1539             | 1.3959                | 0.5702                            | 0.6751                    |
| 9      | 0.1403             | 0.6443                | 0.5498                            | 0.4250                    |
| 10     | 0.1387             | 1.4878                | 0.5616                            | 0.5550                    |

The fuzzy membership values of the 10 non inferior solutions are calculated according to (4) to (16), the result is shown in the above table. The fuzzy membership values of the fifth non inferior solutions are least, so fifth non inferior solutions are chosen as the final optimization results. The results of the improved particle swarm optimization algorithm are compared with the results of the particle swarm optimization and the matlab genetic algorithm toolbox, as shown in table 4.

Table 4. Optimization results comparison of the algorithms

| Comparison object                  | Before optimization | Particle swarm optimization algorithm | Improved particle Swarm optimization algorithm | matlab genetic algorithm toolbox |
|------------------------------------|---------------------|---------------------------------------|-----------------------------------------------|----------------------------------|
| Loss of network /pu                | 0.1609              | 0.1473                                | 0.1354                                        | 0.1388                           |
| Voltage deviation/ pu              | 0.8934              | 0.4261                                | 0.3935                                        | 0.4023                           |
| Static voltage stability margin /pu| 0.5108              | 0.5204                                | 0.5378                                        | 0.5367                           |

It can be seen from table 4 that the optimization results of three target values which are optimized by improved PSO are better than the optimization results of three target values which are optimized by PSO. Compared with the matlab genetic algorithm toolbox, the network loss and voltage deviation are smaller when the improved PSO is used to calculate the optimal solution. As for the optimization effect of static voltage stability margin, the effect of improved PSO and matlab genetic algorithm toolbox is quite.

7. Conclusion

In this paper, the objective of the reactive power optimization model is to minimize the active power loss, minimize the voltage deviation, and maximize the static voltage stability margin. Before the reactive power optimization, the compensation nodes in the standard node system are screened. Through the comparison of data, it shows that the method of choosing reactive power compensation node
presented in this paper is reasonable and effective. The particle swarm optimization algorithm is improved, and the selection pool of global optimal and fuzzy global optimum are introduced, which can effectively reduce the possibility of premature convergence of the algorithm. An improved particle swarm algorithm is used in the IEEE14 standard node system to obtain a set of uniformly distributed Pareto optimal solution sets. Through the calculation of fuzzy membership value, the most optimal result of the non-inferior solution with the least membership value is selected. By comparing with the genetic algorithm toolbox and the standard particle swarm optimization algorithm, the correctness and effectiveness of the proposed method are verified.

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