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Multi-Objective Reactive Power Optimization Based On The Fuzzy Adaptive Particle Swarm Algorithm

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Abstract

To research the problem on the multi-objective reactive power optimization, to utilize the theory of multi-objective fuzzy optimization to change the multi-objective optimization into the single-objective optimization, and to adopt the fuzzy adaptive particle swarm algorithm to carry out solutions. Comprehensively considering the security and economical efficiency of the system, as well as the condition of the operation constraints, to propose a comprehensive and practical multi-objective reactive power optimization model. To consider the multi-objective reactive power optimization model of the voltage stability index can optimize the economic benefit and safety benefit of the system. Applying the theory of multi-objective fuzzy optimization combined with the adaptive particle swarm optimization algorithm to the problem of the multi-objective reactive power optimization could solve the problem of the different dimensional multi-objective optimization in a better way. After adopting the fuzzy adaptive particle swarm algorithm, the superiorities, such as achieving the global optimal solution, reducing the computational complexity, and improving the computational efficiency, are displayed.

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Introduction

The traditional reactive power optimization makes the systemic active power loss as a goal, which satisfies the qualification of the voltage security by providing a range of the node voltage. Among the results of the model optimization established in this way, each node voltage closes with its upper limit, which may bring on a limitation to the output of the reactive power supply, thereby the objective function of the reactive power optimization will conflict with the systemic voltage security. When there is enough margin in the transmission capacity of the system, the consideration of the economic benefit and the basic function constraint condition is proper. However, with the development of the power system, the burden increases rapidly, and the power supply proportion of the distant electrical source increases.

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so at the peak load the transmission capacity may be close to the limit, which increases the possibility of bringing voltage collapse which may become a network accident. Therefore it is necessary to discuss the problem of reactive power optimization in aspects of reducing the active power loss, keeping rational voltage level, and insuring voltage stability, etc.

Considering the multi-objective reactive power optimization can keep the power system working with a better voltage level, a lower transmission loss index and a higher storage of the voltage stability. This is the highest aim of the reactive voltage subject research and the reactive voltage management, which is the basal and important job of ensuring the safe operation of the power system and preventing voltage accident. And it is one of the important jobs for the survival and development of the power system in the market competition.

The essay ensures the qualified rate of the operating voltage, improves the voltage stability and brings the least systemic active power loss, at the same time it establishes a model of the multi-objective reactive power optimization with security and economy. It combines the theory of multi-objective fuzzy optimization with the fuzzy adaptive particle swarm optimization algorithm to the problem of the multi-objective reactive power optimization. It uses the fuzzy set theory to make an optimal integration to the different dimensional multi-objective optimization, to change the multi-objective optimization into the single-objective optimization, and to adopt the fuzzy adaptive particle swarm algorithm to solve the problem of the single-objective optimization.

1. The model of the multi-objective reactive power optimization

The reactive power optimization always adopts the methods of adjusting the generator terminal voltage properly, switching the reactive power compensation, and regulating the transformer taps to reduce the loss in the precondition of ensuring the voltage quality. Its mathematical model is made up of the objective function, power constraint condition, variable constraint condition, etc.

1.1 The objective function

The objective function of the reactive power optimization always considers the following three aspects:

(1) The active power loss
Judging from the economy way, the most adoptive target is the least active power loss:

$$\min P = \sum_{i=1}^{N} G_i (U_i^2 + U_i^2 - 2U_i \cos \theta_i)$$

(1)

(2) The value of the node voltage level is one of the important index of testing the security of the system and the power quality. In the past calculation of the reactive power optimization, the voltage amplitude is usually judged as constraint condition, which always brings the voltage amplitude optimized to its upper limit. Thereby the essay chooses the deviation between the voltage and the assigned voltage as one of the objective function, trying to keep the voltage above satisfaction, which could be shown in the following form:

$$\min \Delta V = \sum_{i=1}^{N} \left[ \frac{V_i - V_i^*}{\Delta V_{\text{max}}} \right]^2$$

(2)

In the formula $V_i$ is the voltage amplitude of the node i; $V_i^*$ is the appointed voltage amplitude of the node i; usually $V_i^* = 1$; $\Delta V_{\text{max}}$ means the largest allowable voltage deviation at the node i; which means $\Delta V_{\text{max}} = V_{\text{max}} - V_{\text{min}}$; and $N_i$ is the load node number of the system.
(3) The system voltage stability

1) The voltage stability index L

The voltage stability index L calculates with the variable and parameter of the load flow. It only needs the voltage information of the load node number and the generator operation data, which has the superiority for an easy calculation. Therefore the least voltage stability index L can be used as one of the objective function, trying to get the largest systemic voltage stability margin, which means:

\[ L_j = \min_{i \in N_j} \left( \sum_{F_jV_i} \right) \quad \text{min } L = \max_j \left( L_j \right) \quad (3) \]

2) The equality constraint condition

The equality constraint condition means the constraint equation of the load flow:

The power constraint of the node number active power is:

\[ P_{Gi} = P_{Di} + \sum_{j \in N_i} V_j \left( G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij} \right) \quad (4) \]

The power constraint of the node number reactive power is:

\[ Q_{Gi} = Q_{Di} + \sum_{j \in N_i} V_j \left( G_{ij} \sin \theta_{ij} + B_{ij} \cos \theta_{ij} \right) \quad (5) \]

3) The inequality constraint condition

In order to ensure the safe operation of the power system, the inequality constraint condition of the reactive power optimization includes:

(1) The node voltage limitation of the generator is:

\[ V_{Gi_{\text{min}}} \leq V_{Gi} \leq V_{Gi_{\text{max}}}, i = 1, \ldots, N_G \quad (6) \]

(2) The range constraint of the transformer tap position change is:

\[ K_{Ti_{\text{min}}} \leq K_{Ti} \leq K_{Ti_{\text{max}}}, i = 1, \ldots, N_T \quad (7) \]

(3) The reactive power compensation, which means the constraint of the reactive facility capacity is:

\[ Q_{Ci_{\text{min}}} \leq Q_{Ci} \leq Q_{Ci_{\text{max}}}, i = 1, \ldots, N_C \quad (8) \]

(4) The node voltage security constraints is:

\[ V_{Li_{\text{min}}} \leq V_{Li} \leq V_{Li_{\text{max}}}, i = 1, \ldots, N_L \quad (9) \]

(5) The range constraint of the generator reactive power is:

\[ Q_{Gi_{\text{min}}} \leq Q_{Gi} \leq Q_{Gi_{\text{max}}}, i = 1, \ldots, N_G \quad (10) \]

In the formulas of (1)-(10), \( P_i \) is the statistical system loss. \( P_a, Q_a \) are the active power and reactive power of the generator at the point of node i. \( P_a, Q_a \) are the loads of the active power and reactive power at the point of node i. \( G_{ij}, B_{ij}, \theta_{ij} \) are the conductance, susceptance and phase difference between the nodes i, j. \( V_i \) is the voltage of the node i. \( N_e, N_e \) are the branch of the participated loss statistic and the set of nodes connected with the node i. \( N_e, N_e, N_e, N_e \) are the number of generators in the system, the node number of the reactive power compensation, the number of the on-load tap changer(OLTC), and the node number of the loads. \( V_{Ti}, Q_{Ti}, K_{Ti} \) is the terminal voltage of generator, the value of the reactive power compensation and the transformer ratio, which is the control variable of the reactive power optimization. Its constraint can make a fulfillment of the boundary control variable. \( V_i, \theta_i, K_{Ti} \) is the voltage of the load node number and the reactive service of the generator, which is the state variable of the reactive power optimization, and its constraint is managed by the penalty function.
1.2 The model of the multi-objective reactive power optimization

Synthetically considered the system economy and the safety index, the reactive power optimization model of the power system is:

$$\begin{align*}
\min & \quad f_1, f_2, f_3 = \min \left[ P_L(x_i, x_j), \Delta V(x_i, x_j), L(x_i, x_j) \right] \\
\text{s.t.} & \quad h(x_i, x_j) = 0 \\
& \quad g(x_i, x_j) \leq 0
\end{align*}$$

In the formula, $h(x_i, x_j) = 0$ is the equality constraint; $g(x_i, x_j) \leq 0$ is the inequality constraint; $x_i$ is the control variable vector, including the terminal voltage of generator end $V_i$, the value of the reactive power compensation $Q_i$, and the transformer ratio $K_i$, which can be shown as:

$$x_i = \left[ V_{Gi}, \cdots V_{NG}, Q_{Ci}, \cdots Q_{NC}, K_{Ti}, \cdots K_{NX} \right]$$

$x_j$ is the state variable vector, including the voltage of the node number $V_{Li}$ and the reactive service of the generator $Q_{Li}$, which can be shown as:

$$x_j = \left[ V_{Li}, \cdots V_{NX}, Q_{Gi}, \cdots Q_{NG} \right]$$

As for the problem of the multi-objective optimization, the essay is trying to calculate in the way of fuzzy solution of the multi-objective optimization which is mentioned above. As for the modal of the multi-objective optimization in the formula of $((4_24)$, it can be changed into the single-objective optimization by the fuzzy solution.

2. The fuzzy adaptive particle swarm algorithm

The fuzzy adaptive particle swarm optimization algorithm uses the local optimum $L_{best}$ to take the place of the global optimum $G_{best}$, the concrete model is:

$$v_{i,d}(t+1) = \chi(v_{i,d}(t) + \text{rand}(0,2)\left(x_{p,d}(t) - x_{i,d}(t)\right) + \text{rand}(0,2)\left(x_{a,d}(t) - x_{i,d}(t)\right))$$

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1)$$

$$\chi = \frac{2}{\sqrt{1+4\text{rho}^2}}$$

In the model, the parameter includes the particle swarm scale $N$, the acceleration coefficient $\Theta_i$ and the scale of the particle neighborhood $R_i$. Bring in the contraction factor $\chi$ to control the speed of the example, which can insure the convergence of the algorithm. The two inputs of the fuzzy inference machine of the fuzzy adaptive particle swarm optimization(FAPSO) are normalized characteristics best present evaluation and the best standardized performance's value, and NCBPE is the best candidate of the PSO algorithm found till now.

$$\text{NCBPE} = \frac{\text{CBPE} - \text{CBPE}_{\text{min}}}{\text{CBPE}_{\text{max}} - \text{CBPE}_{\text{min}}}$$

In order to insure the convergence of the algorithm, according to the literature [6], the controls parameter of the PSO algorithm, $\omega$, $c_1$, and $c_2$, should be retained in the set range, which is $0.2 \leq \omega \leq 1.2, 1.0 \leq c_1 \leq 2.0, 1.0 \leq c_2 \leq 2.0$.

The designing thought mainly comes from the experience of adjusting the controls parameter on line, such as: (1) When the best standardized performance evaluation at present NCBPE becomes very small in the iterative anaphase, the arithmetic can be judged as close to the optimum value, which can reduce
the inertia weight $\omega$, and increase the acceleration coefficient $c_1$ and $c_2$, so that the capacity of the local search can be strengthened. (2) When the iterative times of the normalized characteristics best present evaluation NCBPE staying at the same numerical is large, which means the unvaried iterative times NGUBF of the standardized performance’s value is large, the arithmetic may be converge at a local optimum value. At this time the inertia weight should be increased, and the acceleration coefficient $c_1$ and $c_2$ should be reduced to reinforce the global search ability and dap the local minimums.

Based on the thought mentioned above, the essay brings forward the fuzzy adaptive particle swarm optimization algorithm which is made up of the routine particle swarm optimization algorithm and the parameter fuzzy controller. The function theory is that: according to the best standardized performance evaluation at present and the iterative times of the best unvaried standardized performance’s value, in virtue of the experience to make a fuzzy inference, and the output of the fuzzy controller will be used as the parameter selection in the present PSO arithmetic.

3. The fuzzy solution of the multi-objective optimization

The multi-objective optimal solution is closely related to the optimal solution of each subgoal, including the contribution of each subgoal. But between each subgoal, the relevant relation between the subgoal optimal solution and the multi-objective optimal solution is fuzzy, which is hard to find the bourn. Every solution of the multi-objective optimization design is showing the relation between the multi-objective optimization and each subgoal by a certain relation. Although it can also get the efficient solution or the weak efficient solution, the solution avoiding the fuzziness is dissatisfactory, or even reluctant. I’m going to introduce a fuzzy solution of the multi-objective optimization. Its basic thought is: firstly getting the bounded optimization solution of each subgoal, and using the optimal solution to change the subgoal objective function into fuzziness, and then trying to get the largest solution of the intersection membership function. The solution is the optimal solution of the multi-objective optimization. The concrete step of the multi-objective fuzzy optimization is:

As for the model of the multi-objective reactive power optimization in the formulas of (14), (15), (16), the functions of $f_1(x)$, $f_2(x)$, $f_3(x)$ is supposed according to the membership functions of $\mu_1(x)$, $\mu_2(x)$, $\mu_3(x)$, this problem can be changed into the following problems:

![Fig. 1 the program algorithm flow](image-url)
In this way the primary the problem of the multi-objective optimization will be changed into the single-objective optimization. By getting an optimal subordinate $H_{opt}$, we can achieve a harmony among each objective function. $p_{opt}$ means the satisfaction of each objection optimized at the same time. There are many kinds of membership function, for the simpleness, the essay is using the linearity membership function.

1) The membership function of the objective function $f_1$ is:

$$
\mu(P_{\text{loss min}}) = \frac{P_{\text{loss max}} - P_{\text{loss min}}}{P_{\text{loss max}} - P_{\text{loss min}}}
$$

In the formula $P_{\text{loss min}}$ is the optimal solution when the network loss is set as the single object. $P_{\text{loss max}}$ is the network loss of the system without reactive power compensation.

2) The membership function of the objective function $f_2$ is:

$$
\mu_{\Delta V} = \frac{\Delta V_{\text{max}} - \Delta V}{\Delta V_{\text{max}} - \Delta V_{\text{min}}}
$$

In the formula $\Delta V_{\text{max}}$ is the largest voltage deviation which is allowed by the system. $\Delta V_{\text{min}}$ is the optimum value when the voltage deviation is set as the single object.

3) The membership function of the objective function $f_3$ is:

$$
\mu_{L} = \frac{L_{\text{max}} - L}{L_{\text{max}} - L_{\text{min}}}
$$

In the formula $L_{\text{max}}$ is the largest voltage stability index which is allowed by the system. $L_{\text{min}}$ is the optimum value when the voltage stability index is set as the single object.

4. Example simulations

It combines the theory of multi-objective fuzzy optimization with the fuzzy adaptive particle swarm optimization algorithm to the problem of the multi-objective reactive power optimization. Firstly it uses the fuzzy set theory to make an optimal integration to the different dimensional multi-objective optimization, to change the multi-objective optimization into the single-objective optimization, and to adopt the fuzzy adaptive particle swarm algorithm to solve the problem of the single-objective optimization. The progress of getting the solution of the multi-objective reactive power optimization model mainly includes:

Read in the original data, which includes the power flow calculation data, the description of the reactive power control variable, and all kinds of constraint condition.

Based on the multi-objective reactive power optimization mathematic model and the fuzzy solution, change the multi-objective problem into the single-objective optimization.

Using the FAPSO solution mentioned above to solve the problem of single-objective optimization.

In order to test the FAPSO solution and to consider the correctness and validity of the voltage stability index of the multi-objective reactive power optimization model, the system calculates a reactive power optimization at the node of IEEE 30. It compares the result with the optimized results of the single particle swarm optimization and the genetic algorithm.
The programming of Visual C++ language is a reactive power optimization calculate program. It uses 100 as the constringency basis, and runs for many times. The node of IEEE 30 of the system data is unchangeable. The voltage of the PV node and slack bus is set as 0.90-1.10, and the voltage of the PQ node is set as 0.95-1.05.

Parts of the average results are shown in the table 1. the loss after the reactive power optimization is brought down from 5.51MW to 4.95MW, the amplitude reduction is 10.16%. Its result is obviously better than that of PSO and SGA. In the initial power flow of the system, the voltage of 3 nodes is beyond the lower limit: V26=0.932, V29=0.940, V30=0.928. After the optimization all the optimal solutions conquers the voltage instability, including the output of the generator.

<table>
<thead>
<tr>
<th>Item Name</th>
<th>initial state</th>
<th>FAPSO Optimization result</th>
<th>PSO Optimization result</th>
<th>SGA Optimization result</th>
</tr>
</thead>
<tbody>
<tr>
<td>network loss (p.u.)</td>
<td>0.0551</td>
<td>0.0495</td>
<td>0.0516</td>
<td>0.05268</td>
</tr>
<tr>
<td>voltage deviation</td>
<td>0.0319</td>
<td>0.0110</td>
<td>0.0160</td>
<td>0.0176</td>
</tr>
<tr>
<td>voltage stability index</td>
<td>0.1579</td>
<td>0.1238</td>
<td>0.1307</td>
<td>0.1387</td>
</tr>
<tr>
<td>drop rate of the network loss(%)</td>
<td>--</td>
<td>10.16</td>
<td>6.35</td>
<td>4.39</td>
</tr>
<tr>
<td>voltage qualified rate(%)</td>
<td>90</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Judging from the average convergence specialty of FAPSO and PSO in picture 3 and picture 4, as for the systemic network loss and the voltage stability index, PSO is too premature to converge at a local extremism, and FAPSO can search a better target value. In picture 5, judging the distributing of the voltage amplitude of before-after optimization, the after one avoids the situation of voltage instability, and the voltage of each node is in the prescribed range.
In order to review the infection of the particle swarm scale on the optimization result, in the circumstances of keeping the other parameter invariable, use different particle swarm scale to optimize the same problem. Judging from the results in the table 2, with the accretion of the particle swarm scale, its optimum solution quality is improved, but the time need for the optimization is improved at the same time. Therefore we should use proper particle swarm scale for different problem.

Table 2 The optimum result and average calculating result of different particle swarm scale

<table>
<thead>
<tr>
<th>The particle swarm scale</th>
<th>The calculation time(s)</th>
<th>active power loss(p.u.) optimum result</th>
<th>average result</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>2.7</td>
<td>0.048343</td>
<td>0.050809</td>
</tr>
<tr>
<td>30</td>
<td>6.6</td>
<td>0.048227</td>
<td>0.050126</td>
</tr>
<tr>
<td>50</td>
<td>11.3</td>
<td>0.047851</td>
<td>0.049666</td>
</tr>
<tr>
<td>80</td>
<td>18.9</td>
<td>0.047950</td>
<td>0.049569</td>
</tr>
<tr>
<td>100</td>
<td>24.7</td>
<td>0.047892</td>
<td>0.049340</td>
</tr>
</tbody>
</table>

5. Conclusion

To establish a power grid model of the multi-objective reactive power optimization with stability and economy. The model considers the network loss, the voltage level and the voltage stability index. After adopting the fuzzy adaptive particle swarm algorithm, the superiorities, such as achieving the global optimal solution, reducing the computational complexity, and improving the computational efficiency, are displayed.
Reference literature:


