Application of Optimization Algorithm on Simulating the Fisher Fishing in Multi-objective Optimal Reactive Power

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Abstract

Optimization algorithm on simulating the fisher fishing (SFOA) is a novel optimization algorithm, it was presented based on simulating the behavior and habit of fisher’s fishing. By the algorithm, and algorithm for solving the power system SFOA multi-objective reactive power optimization (ORP) problem. The model of ORP included line loss and average voltage offset as optimal target, and the method that can transform target function to constraint based on user reference region was proposed. ORP was optimization problem with multi-variable, and optimization speed of SFOA would be exposed to restrict. So the method that randomly initialized in the their cube was adopted, which could simply moving search and shrinking search in the cube and improve searching speed. The simulation results for IEEE-30 nodes and IEEE-57 nodes system showed that SFOA had global search performance and steady convergence rates, which could improve the economics and safety of power system effectively.

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Keywords: simulating fisher’s fishing optimization algorithm; moving search; shrinking search; multi-objective; optimal reactive power

1. Introduction

With the growing size of the power system, accidents are increasing due to the improper distribution of reactive power system, therefore, reactive power optimization has become increasingly important. The so-called reactive power optimization of power system refers to giving the parameters and load of the network structure, the full use of the power system reactive power, improve the voltage quality, reduce network losses. Reactive power optimization problem is a typical nonlinear programming problem, with many variables, multiple constraints, nonlinear, discontinuous, etc., in this area, there are already many intelligent algorithms including genetic algorithm, evolutionary algorithm, PSO[1-3], etc. using in reactive power optimization and achieved certain results.

Via the observation on casting net of fisherman, [4] proposed a optimization algorithm that simulates the behavior and habit of fisher fishing. This paper use this strategy to optimal the reactive power of power system for the first time, and through testing the IEEE-30 nodes and the IEEE-57 nodes of numerical
examples, it shows that the algorithm used in multi-objective reactive power optimization is feasible and effective.

2. Mathematical model of reactive power optimization

A. Objective Function

Reactive power optimization refers that make full use of the reactive power by regulating the generator terminal voltage, adjust the transformer turns ratio and compensation capacitor switching control variables, and then minimize the voltage to the whole network of qualified and active power. Optimization of power system usually pursues two objectives: technical objectives and economic goals. The goals should also be pursued by reactive power optimization, but generally only consider the reactive power optimization of economic goals, namely, the smallest network loss. As the pursuit of the objective function only minimize loss, while the loss is strongly coupled with high and low voltage (ie, increase voltage can effectively reduce the loss), Therefore, the final optimization of reactive power optimization results given node voltage values are generally higher than the values before optimization. It leads that with smallest loss, the voltage of network will closely reach the upper limit, which would threaten network security. With considering the minimum loss, this reactive power optimization introduces the average voltage deviation as another target.

1) Power Loss

\[
\min f_1 = P_{loss} = \sum_{k=1}^{N_k} G_k(i,j)[V_i^2 + V_j^2 -2V_iV_j \cos \theta_{ij}] \tag{1}
\]

\(N_k\) is the system circuits number; \(G_k(i,j)\) is the conductance of \(k\)th branch circuit; \(V_i, V_j\) are the voltage amplitude of the nodes; \(\theta_{ij}\) is the phase angle difference between nodes i and j.

2) Average voltage deviation is

\[
\min f_2 = V_{av} = \frac{\left(\sum_{i=1}^{N} |V_i - V_i^*| \right)}{N} \tag{2}
\]

\(N\) is nodes number; \(V_i\) is the actual voltage of ith node; \(V_i^*\) is nominal voltage of node i.

2.1 Power equation constraints

In reactive power optimization model, the node active and reactive power constraints is

\[
\begin{align*}
P_{Gi} - P_{Di} - V_j \sum_{j \in N} V_j (G_j \sin \theta_{ij} + B_j \cos \theta_{ij}) &= 0, \quad i \in N_{PQ} \tag{3} \\
Q_{Ci} + Q_{Di} - V_j \sum_{j \in N} V_j (G_j \sin \theta_{ij} - B_j \cos \theta_{ij}) &= 0, \quad i \in N_{PQ} \tag{4}
\end{align*}
\]

2.2 Variables constraints

Reactive power optimization variable constraints can be divided into control variables and state variables bound constraints. Generator terminal voltage \(V_{Gi}\), node capacity of reactive power compensation \(Q_{Ci}\), and transformer tap \(T_{ki}\) are the control variables. Reactive power of generator \(Q_{Gi}\) and load voltage \(V_i\) are the state variables.

The control variables constraint is

\[
\begin{align*}
V_{Gi\min} \leq V_{Gi} \leq V_{Gi\max}, \quad i \in N_G \\
Q_{Ci\min} \leq Q_{Ci} \leq Q_{Ci\max}, \quad i \in N_C \\
T_{ki\min} \leq T_{ki} \leq T_{ki\max}, \quad i \in N_T
\end{align*}
\]
The state variables constraints is

\[
\begin{aligned}
&Q_{G_{i_{\min}}} \leq Q_{G_{i}} \leq Q_{G_{i_{\max}}}, i \in N_G \\
&V_{i_{\min}} \leq V_{i} \leq V_{i_{\max}}, i \in N
\end{aligned}
\]  

\[ (6) \]

\( N_G, N_C, N_T, N \) are the nodes set of generators, the compensation capacitor nodes set, transformer branches set and nodes set respectively; \( V_{G_{i}}, V_{G_{i_{\max}}}, V_{G_{i_{\min}}} \) are generator’s voltage and its upper and lower limits; \( Q_{G_{i}}, Q_{G_{i_{\max}}}, Q_{G_{i_{\min}}} \) are reactive power compensation capacity and upper and lower limits; \( T_{k_{i}}, T_{k_{i_{\max}}}, T_{k_{i_{\min}}} \) are transformer tap position and the upper and lower limits; \( Q_{G_{i}}, Q_{G_{i_{\max}}}, Q_{G_{i_{\min}}} \) are generator reactive power output and upper and lower limits; \( V_{i}, V_{i_{\max}}, V_{i_{\min}} \) are the voltage amplitude and its upper and lower limits of node \( i \);

3. Fisher Fishing simulation optimisation Algorithm

Fisherman casting a net fishing on the river began a little casually cast nets, and then under the current position spread around once again the position. In addition, the fisherman always hope to catch as many fishes every time, which depends on fish density of current location. Therefore choosing the casting nets position is based on the following criteria: 1) casting in the position that fish density is high; 2) moving the casting net position forward to a new one that density is higher; 3) to seek the optimal position, fisherman will not cast net in one position more than one time; 4) contract the net if a high density position is found, hoping to “catch them all”.

Based on the imitation of the behavior of fisher fishing, there comes up a new search method about fisher fishing. At first, the method randomly chooses several points in search space; and then construct a cube centered by each chosen point (i.e. every fisherman casts a net around himself); At last, each point will implement the mobile search and contracted search respectively according to one’s environment and the final global optimal solution will be obtained. In summary, the search algorithm proposed by Wang [4] gets the global optimal solution uses mainly two basic strategies, mobile search and contracted search.

Let \( \Omega = \Omega_1 \times \Omega_2 \times \cdot \cdot \cdot \times \Omega_n \) be the closed area (fishing area), \( X = (x_1, x_2, \ldots, x_n) \in \Omega \) the state of the procedure, \( x_j \in \Omega_j = [a_j, b_j] \) \((j = 1, 2, \ldots, n)\), \( f(x) \) be the fish density function (objective function) and it is continuous. The goal fisherman would achieve is to find the area the density is the highest.

At beginning, there are arbitrary \( k \) fisherman, the casting position of fisherman \( i \) is \( P_{0_{i}} = (x_{0_{i1}}, x_{0_{i2}}, \ldots, x_{0_{in}}) \). \( i = 1, 2, \ldots, k \) Fisherman \( i \) will try to cast nets up and down, left and right and back and forth of \( P_{0_{i}} \), and it will have the casting position set

\[
\Omega_{0_{i}} = \{ X_{0_{i}} = (x_{0_{i1}}, x_{0_{i2}}, \ldots, x_{0_{in}}) | x_{0_{ij}} \in [x_{0_{ij}} - l_{ij}^{-}, x_{0_{ij}} + l_{ij}^{+}], j = 1, 2, \ldots, n \}
\]

\[ (7) \]

If \( f(X_{0_{i}}^{(0)}) = \max_{X^{(0)} \in \Omega_{0_{i}}} f(X^{(0)}) < f(P_{0_{i}}^{(0)}) \), then fisherman will do the mobile search described above; if \( f(X_{0_{i}}^{(0)}) = \max_{X^{(0)} \in \Omega_{0_{i}}} f(X^{(0)}) \geq f(P_{0_{i}}^{(0)}) \), and \( x_{0_{ij}}^{(0)} \neq P_{0_{ij}}^{(0)} \), \( t = 1, 2, \ldots, k \), fisherman \( i \) will move to the position \( P_{1_{i}} = X_{0_{i}}^{(0)} \) and let \( P_{1_{i}}^{(0)} \) be the new center to cast nets around, it has the new casting position set

\[
\Omega_{0_{i}}^{(0)} = \{ X_{0_{i}}^{(0)} = (l_{1_{i}}^{(0)}, l_{2_{i}}^{(0)}, \ldots, l_{n_{i}}^{(0)}) | x_{0_{ij}}^{(0)} - l_{ij}^{-}, x_{0_{ij}}^{(0)} + l_{ij}^{+}], j = 1, 2, \ldots, n \}
\]

\[ (8) \]
\[ t^{(-)}_j = \alpha t^{(-)}_j , \quad t^{(+)}_j = \alpha t^{(+)}_j, \quad 0 < \alpha < 1. \]

\[ t^{(-)}_j = \alpha t^{(-)}_j , \quad t^{(+)}_j = \alpha t^{(+)}_j, \quad 0 < \alpha < 1. \]

\[ t^{(-)}_j = \alpha t^{(-)}_j , \quad t^{(+)}_j = \alpha t^{(+)}_j, \quad 0 < \alpha < 1. \] After contracted search, fisherman \( i \) will repeatly implement the algorithm above in order to search the optimal solution. All \( k \) fisherman will use this method to search the extreme region and even the extreme points. To ensure the \( k \) fisherman will not search one position more than once, it set up a publicity board, so that each fisherman can know the current best location and search path of each fisherman.

In order to exclude possible infinite loop condition in search procedure, there set up a threshold of contraction operation, which is \( CN \). If a fisherman’s contraction operation time is over threshold \( CN \) in one position, and movement operation time is not more that \( N \), then the fisherman will implement the mobile search instead.

### 4. Exploit User preference area to convert objective function into constraints

In the past, the multi-objective optimization with the optimal solution is a difficulty, the main problem is more goals are interdependent and the optimization results aren't the same dimension, with the method of multi-objective distribution into single objective, optimization brings the problem of rational distribution of weights, weights allocation whether reasonable directly affect the final result of optimization. In recent years, several treatment of multi-objective optimization methods are proposed, mainly pareto optimality set\(^{[5-7]}\) and clustering analysis\(^{[8-9]}\). These two kinds of methods of weighted value method is simpler than ever more effective treatment of conflict between multiple targets, improve the quality of the optimal solution.

There are only two objective functions, if use pareto optimality sets and clustering analysis to get the optimal solution, it would affect optimization efficiency. Through the analysis of the relationship between this two objective, put forward a method that convert the objective function into constraints based on user preference area, and the original multiple objective optimization become a single one.

User preference area is defined as follows

\[ D = \prod_{j=1}^{k} [a_j, b_j], \quad a_j \leq b_j (j = 1, 2, \ldots, k) \quad (9) \]

When solution of these area is found or close to be found in implementation of the algorithm, deal with the fitness of the objective function properly, to let the solution be optimal as possible.

The average voltage is converted into constraint, user preference is \( V_{av} \in [0, 0.02] \), regard this as constraint to prevent a solution of smaller average loss deviation and larger average voltage become the optimal one. The objective function can be expressed as

\[ \min F = f_i * h(V_{av}) \quad (10) \]

\[ h(V_{av}) \quad (11) \]

Multiple objective optimization is converted into single objective optimization in (11), and the optimization function is in the same dimension, it solve the multi-objective optimization in solving the optimal of the difficulties simply and effectively.

### 5. The fisher fishing simulation optimization algorithm in the application of reactive power optimization
When SFOA algorithm implements mobile search and contracted search, fisherman must cast nets one time for each direction. It is easy in two-dimension variables, but the reactive power optimization is high-dimension, according to the strategy described as above, the search speed will not satisfy the demands of power system. In the comprehensive consideration of the above requirements, as take the search strategy of the algorithm, makes following processing to the algorithm optimization method: each variable constructs the cube taking itself as the center, the body of cube carries on the mobile search. Reactive power optimization variables in the cube randomly choose P variables to optimize search, if better variables are found, it will do the contracted search, namely, construct a small cube taking the better variables as new center, and initially choose P variables randomly to optimize again, repeat the steps above.

Reactive power optimization variables that are continuous variables and discrete variables, during mobile search and contracted search of SOFA, the search step length should be set respectively, for mobile search, the continuous variables, \( l_i^+ = -l_i^- = 0.03 \), and discrete variables \( l_i^+ = -l_i^- = 2 \), when \( \alpha \) is continuous variable, it sets to be \( \text{rand}(\alpha) \cdot l_i^+ \), and \( [\text{rand}(\alpha) \cdot l_i^-] \) when discrete variable. (\( \text{rand}(\cdot) \) refers to the random 0 and 1,\([\cdot]\) refers to round-off)

Through the analysis above, the steps of SOFA for multi-objective reactive power optimization could be list as

1) Input the raw data of the network;
2) Initialize the positions of fisherman, namely the control variables;
3) Find the best fishing position of each fisherman, and publish on the publicity broad;
4) Mobile search of each fisherman;
5) Judge whether better position is found during mobile search, if yes, go to the step 6), or go to 4) else;
6) Modify the best position on the publicity broad, judge if it is over the contraction operation threshold \( CN \), if yes, go to the step 8), or carry on contracted search else;
7) Judge if better position is found during contracted search, if yes, turn back to step 6), and else turn to step 8);
8) Judge if the iteration reach the threshold \( N \), if yes go to 9), or 4) else;
9) Output the result. End.

6. Example analysis

In this example, the parameters are set as, original fisherman number \( K=30 \), mobile search threshold \( N = 300 \), contracted search threshold \( CN = 10 \), the specific node parameters of IEEE 30 can be seen in [11]. The initial net loss is 0.0572, the initial voltage average deviation value is 0.0247, the node voltage bound is 1.05 and 0.95, power datum is \( S_B=100 \text{ MVA} \).

According to [11], comparison among GA, PSO, SSFOA, MSFOA of IEEE 30 is listed in Tab.1. Tab.1 shows that the result precision of SOFA is better than that of GA and PSO, SOFA is feasible and effective for reactive power optimization.

<table>
<thead>
<tr>
<th></th>
<th>PSO</th>
<th>GA</th>
<th>SSFOA</th>
<th>MSFOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{loss} )</td>
<td>0.0546</td>
<td>0.0533</td>
<td>0.0517</td>
<td>0.0517</td>
</tr>
<tr>
<td>( V_a )</td>
<td>0.026</td>
<td>0.0039</td>
<td>0.0055</td>
<td>0.055</td>
</tr>
<tr>
<td>( n_{save%} )</td>
<td>4.5</td>
<td>6.88</td>
<td>9.61</td>
<td>9.61</td>
</tr>
</tbody>
</table>

Tab.1 lists the five independent running comparison of SOFA in single objective and multiple objective for reactive power optimization. It shows that, 1. when computing similar net losses, iteration
time of multi-objective is larger than the single; 2. when the net losses are closed, the average voltage deviation value of multi-objective is far smaller than that of the single.

Tab.2 the results of five times computation for IEEE 30 buses system

<table>
<thead>
<tr>
<th></th>
<th>SSFOA</th>
<th>MSFOA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time</td>
<td>P_{loss}</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td>0.0519</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0.0520</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>0.0518</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0.0519</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>0.0517</td>
</tr>
</tbody>
</table>

When net loss is 0.0517, the voltage distribution plot of SOFA for single objective and multi-objective is showed in Fig.1. We can see that deviation for rated voltage of multi-objective reactive power optimization is smaller that single objective obviously, it improves the voltage quality, and ensure the safe operation of power grid. It also demonstrates that use of user preference region to convert objective function into constraints ensures the smallest net losses and average voltage deviation, it solves the multi-objective optimization simply and effectively.

Fig.1 The curves of voltage distribution for IEEE 30 buses system

The comparison between SSOFA and MSOFA in reactive power optimization of IEEE 57 is in Tab.1. The iteration of SOFA for single objective is 97, convergence rate is fast, and net loss is reduced from 2788 to 2578, it is down 7.53 percents, but high voltage deviation is not conductive to the security of grid operation; for multi-objective, the convergence rate and precision of SOFA is not as good as single objective, but the voltage deviation is smaller, it is useful for the sake of security, and the reduction rate is over 5 percents. SOFA is fit for single objective and multi-objective optimization, it has a nice prospect of online application.

Tab.3 The optimized results of IEEE 57 buses system

<table>
<thead>
<tr>
<th></th>
<th>P_{loss}</th>
<th>V_a</th>
<th>\eta_{save}%</th>
<th>Average Ite.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ORIGINAL</td>
<td>0.2788</td>
<td>0.0242</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SSOFA</td>
<td>0.2578</td>
<td>0.0324</td>
<td>7.53</td>
<td>97</td>
</tr>
<tr>
<td>MSOFA</td>
<td>0.2647</td>
<td>0.0204</td>
<td>5.05</td>
<td>175</td>
</tr>
</tbody>
</table>

Fig.2 demonstrates the original voltage and the single objective, multi-objective reactive power optimization distribution plot. There are some original voltage in the illegal region, and after optimization,
all node voltage was in the legal area, and voltage of multi-objective is closed to the rated value, the average voltage deviation is smaller than the single. So, SOFA works well in single objective and multi-objective reactive power optimization in power system.

7. Conclusions

SOFA is a novel intelligent algorithm, it has good global search performance, and stable search rate. When used in reactive power optimization in power system, it could obtain the optimal solution in feasible region. From the comparison of the result of single objective and multi-objective, it shows that, in adding minimizing the average voltage deviation, the optimal results reduce the deviation obviously. It increase the security as optimization.

Reference

