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Power system reactive power optimization based on MIPSO

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Abstract

In order to improve power quality and reduce network losses, this paper proposes a modified immune particle swarm algorithm for power system reactive power optimization. To overcome the disadvantages in the traditional PSO algorithm about low accuracy and easy to fall into local optimal, MIPSO adopts sinusoidal changing inertia weight strategy to make particles explore the local and global optimization more efficiently. Introduce convergence acceleration factor to improve the convergence rate. Modified immune principle enhances the search capability to avoid premature convergence. Finally, compare the reactive power optimization results of Wuzhong of Ningxia system by MIPSO with other classical PSO algorithms. The experimental results show that the MIPSO algorithm is an efficient and feasible approach for reactive power optimization.

Keywords: reactive power optimization, particle swarm algorithm, sinusoidal changing inertia weight, convergence acceleration factor, modified immune

1. Introduction

WITH the development of the power system, reactive power optimization has become an indispensable approach to guarantee the reactive power balance and to improve grid reliability and security. The researchers hope to maintain the system voltage level, reduce active power losses and improve the reliability of power system through reasonable distribution and optimization of reactive power flow. Reactive power optimization, which belongs to a part of optimal power flow (OPF), is a kind of complicated and combined continuous variables with discrete variables, dynamic, multi-targets, multiple constraints and nonlinear optimization problem.

Over the years, reactive power optimization has always been a central issue. A variety of reactive power optimizations have been proposed successively. Since 1995, particle swarm optimization [1] (PSO) proposed by Eberhart and Kennedy. As a new heuristic search algorithm, this method shows its broad

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prospect in resolving reactive power optimization. The paper [2] proposes a multi-agent particle swarm optimization (MAPSO) to optimize the reactive power. The paper [3] applies standard PSO algorithm to the dynamic reactive power optimization, establishing a dynamic reactive power optimization model. Based on conventional PSO algorithm, the paper [4] puts forward an adaptive PSO algorithm, improving the convergence of the algorithm by changing the parameters automatically. However, there are still many disadvantages in PSO algorithm, such as slow convergence in the later stage, rapid decline in particle diversity with generations and easy to fall into the local premature convergence.

This paper proposes a new convergence acceleration factor and modified immune principle combined particle swarm optimization for reactive power optimization by adopting the sinusoidal changing inertia weight strategy. This method, called MIPSO algorithm, has a faster convergence rate and better particle diversity comparing with other algorithms, avoiding premature convergence phenomenon and improving the search ability of the algorithm greatly.

2. Mathematic Modelof Reactive Power Optimization

The reactive power optimization is on the premise of known active power scheduling, through optimization to get the best reactive power distribution to determine the value of control variables, allowing the system to meet the various operating constraints and some indicators (such as the minimum active power loss, the minimum compensation capacitor, the best compensation, etc) to achieve the best. Reactive power optimization is a kind of dynamic, multi-targets, multiple constraints and nonlinear optimization problem which combines continuous variables with discrete variables.

Reactive power optimization model [5,6] contains the power constraint equations and variable constraint equations. This paper selects the minimum active power loss as the objective function, generator reactive power and load node voltages as state variables, the node voltage generator, transformer ratio and reactive power compensation capacity as control variables. Determining the generator terminal voltage, under-load tap-changing transformer taps and the parameters of reactive compensation equipment can change the reactive power flow distribution and reduce network loss. Detailed mathematical model is as follows.

The state variables should be written in the form of penalty function. The extended objective function is as follows:

$$\min F = P_{Loss} + \lambda_1 \sum_{i=1}^{N_L} \left(\frac{\Delta V_i}{V_{i\max} - V_{i\min}}\right)^2 + \lambda_2 \sum_{j=1}^{N_g} \left(\frac{\Delta Q_{Gj}}{Q_{Gj\max} - Q_{Gj\min}}\right)^2 \tag{1}$$

in which: P_{Loss} is the system active power loss; λ_1 is the penalty factor of load bus voltage out of range; λ_2 is the penalty factor of generator reactive power out of bound; N_L is the total number of load nodes; N_G is the total number of generator nodes; V_i, V_{imax}, V_{imin} is load bus voltage, voltage upper and lower limit respectively; Q_j, Q_{jmax}, Q_{jmin} is generator reactive power output, output upper and lower limit respectively; P_{Loss} , ΔV_i andΔQ_j can be obtained by equations (2)- (4).

$$P_{Loss} = \sum_{k=1}^{N_e} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \tag{2}$$

$$\Delta V_i = \begin{cases} V_i - V_{i\max}, & V_i > V_{i\max} \\ 0, & V_{i\min} < V_i < V_{i\max} \\ V_{i\min} - V_i, & V_i < V_{i\min} \end{cases} \tag{3}$$

Control constraints equations are as follows:

$$\begin{cases} V_{Gi\min} \le V_{Gi} \le V_{Gi\max} \quad , \quad i = 1,2,...,N_g \\ Q_{Cj\min} \le Q_{Cj} \le Q_{Cj\max} \quad , \quad j = 1,2,...,N_c \\ T_{k\min} \le T_k \le T_{k\max} \quad , \quad k = 1,2,...,N_t \end{cases} \tag{4}$$

in which Nc, Nt is the total number of reactive compensations and the total number of transformer taps.

3. Modified Immune PSO(MIPSO)

3.1. Particle codes

As the output of reactive power compensation equipment and the ratios of adjustable transformer are discrete, while the generator node voltages are continuous, this paper adopts decimal integer and real number hybrid coding system. Hybrid coding does not require optimal discrete variable for regulation, nor reduces the range of optimization for the sake of continuous variable segments.

In reactive power optimization, the discrete variable that the switching capacity of reactive power compensation equipment and the ratio of under-load tap-changing transformers can be converted to continuous integer variables according to certain step through the mapping method. Assume a set of potential space solutions (5) are as follows:

$$X = [V_{G1}, V_{G2}, ..., V_{GN_g}, K_{C1}, K_{C2}, ..., K_{CN_c}, M_{T1}, M_{T2}, ..., M_{TNt}] \tag{5}$$

$$Q_{Ci} = K_{Ci} \times S_{Ci} \tag{6}$$

$$T_{tm} = T_{i\min} + M_{Ti} \times S_{Ti} \tag{7}$$

Where: Kci is the switching gear corresponding to the switching capacity of reactive-load compensation equipment, which is positive for capacitive reactive power device and negative for inductive reactive power device; S_{ci} is the step size of the switching equipment; M_{Ti} is the gear of regulating transformer ratio; S_{Ti} is the step size of transformer ratio gear.

3.2. Sine inertia weight adjustment

Since the standard PSO algorithm has many drawbacks, for example, easy fall into premature convergence, low accuracy and easily divergent. When the inertia weight ϖ is large, it is conductive to global search; when the inertia weight ϖ is small, it is conductive to local search. This paper adopts sine inertia weight to improve the performance of PSO algorithm.

Equations (5) and (6) indicate that the changes of particles' velocity and position are second-order differential equations, i.e.:

$$v_{id}^{t+2} + (c_1 r_1 + c_2 r_2 - 1 - \varpi) v_{id}^{t+1} + \varpi v_{id}^{t} = 0 \tag{8}$$

$$x_{id}^{t+2} + (c_1 r_1 + c_2 r_2 - 1 - \varpi) x_{id}^{t+1} + \varpi x_{id}^{t} - c_1 r_1 p_{id}^{t} - c_2 r_2 p_{gd}^{t} = 0 \tag{9}$$

The stability of the particle velocity change has a great influence on the entire particle swarm in the optimizing. When the velocity of particle reaches infinity, the trajectory is divergent and will lead the entire particle swarm trajectories to divergent.

3.3. Modified immune strategy

The PSO algorithm process is a process of decreasing particle diversity, easily to fall into premature convergence. To increase the diversity of the population, this paper proposes a modified immune PSO based on PSO. The basic idea is as follows: in iteration, if the algorithm blocks and the population diversity is bad, that is p_g does not change for M generations, it needs to introduce a modified immune strategy for production of new particle swarm. The swarm size is N, in which N/2 of particles are obtained by new strategy, the other N/2 are obtained by immune strategy.

The aim of new strategy is to solve the problem of optimizing space density, increasing the new search space. This strategy is indeed a mutation, which expand the diversity of population and make particles escape from the local maximum value of 'premature convergence', so as to optimize the accuracy and convergence of the algorithm.

In the new generation, the other N/2 particles are obtained by immune strategy. The simulation principle of immune strategy[11] includes: immune recognition, immune memory and antibody concentration inhibition. Immune recognition is an intelligent reinforcement learning process, which can extract the characteristics of the antigen and save the best antibody into the immune memory cell bank. When come across a new antigen, the immune system needs more time to respond, but when encounters again, the answer is very fast and can produce high affinity antibodies to remove pathogens. In order to avoid premature convergence, this paper introduce antibody concentration inhibition mechanism and propose a immune principle —inhibit the antibodies with high concentration and low affinity， promote the antibodies with low concentration and high affinity to enhance the diversity of population.

The affinity equation of the *i-th* antibody is as follows:

$$A(i) = \frac{1}{\sum_{j=1}^{M} \sqrt{\sum_{k=1}^{D} (P_{g_{ik}} - P_{g_{jk}})^2}} \tag{10}$$

First, immune strategy saves Pg of each iteration into memory cell through immune recognition. Then calculate the antibody affinity through equation (10). Finally, select N/2 individual particles to form a new population based on immune principle.

3.4. Procedures of MIPSO

Step 1: Set the swarm size as N and initialize the particle swarm to obtain velocity and position of each particle.

Step 2: Calculate the fitness of each particle.

Step 3: Calculate the current number of iteration t, t=t+1.

Step 4: For each particle, by comparing the current fitness value and fitness extreme value and comparing the global fitness value and global fitness extreme value, choose the best fitness value as the particle individual fitness extreme value and global fitness extreme value.

Step 5: Generate memory cells, save the fitness extreme value into cell bank.

Step 6: Determine whether the global fitness extreme value with continuous M generations does not change. If so, then go to step 7; otherwise to step 8.

Step 7: Adopt modified immune strategy to enhance the particle swarm diversity, producing a new generation of N particles.

Step 8: Determine whether the termination condition meets or not. If so, end the algorithm, otherwise go to step 2.

4. Numerical results

The system parameters are set as follows: the precision of power flow is $pr = 10^{-6}$; the population scale is N=100; the maximum iteration number is $T_{\max} = 400$. Calculate the optimal results of Wuzhong power grid under 4 typical operation modes and compare the results to those before optimization. The results are shown in Table 1.

Table 1. The comparison of the reactive power index results before and after optimization of Wuzhong power grid under 4 typical operation modes

Operation mode	Network loss(MW, Mvar)		The capacity of reactive power	
	Before optimization	After optimization	Before optimization	After optimization
Summer max	97.26+35.08j	90.00+29.73j	273.05	288.48
Summer min	90.37+32.56j	84.23+25.91j	295.64	307.57
Winter max	89.66+35.42j	80.58+31.09j	310.27	318.63
Winter min	88.05+27.08j	85.67+24.96j	325.69	331.58

From the table above, under a variety of operation modes, the system active power loss and reactive power loss both has reduced and the reactive capacity has increased after the reactive power optimization. In the 4 operation modes, the loss of the minimum operation mode in winter is minimum and reactive capacity is maximum, while the loss of the maximum operation mode in summer is maximum and reactive capacity is minimum.

Compare the active power loss calculated by using proposed MIPSO with that of genetic algorithm, chaotic algorithm, Box algorithm, PSO algorithm and so on, the result indicates that MIPSO is effective. The results are shown in Table 2.

Table 2. Compare the active power loss of Wuzhong power grid calculated by different algorithm under maximum operation mode in summer

Optimization algorithm	Active power loss(MV）
Initial standard power grid	97.26
PSO algorithm	96.12
chaotic algorithm	95.70
Box algorithm	93.57
PSO algorithm	92.23
MIPSO(in this paper)	90.00

5. Summary and conclusions

In order to ensure the power quality and enhance the grid security and economy, the importance of reactive power optimization stands out. Research on reactive power optimization algorithm has drawn a lot of attentions. PSO algorithm provides a fantastic solution to solve large-scale non-linear, multivariable, non-differentiable and multi-peak optimization problem. To overcome the disadvantages in the traditional

PSO algorithm about low accuracy and easy to fall into local optimal, this paper proposes a PSO-based modified immune PSO. This algorithm adopts sinusoidal changing inertia weight strategy and introduces a convergence acceleration factor. Moreover, a modified immune strategy is proposed to improve the global search capacity. Finally, compare the reactive power optimization result of Wuzhong of Ningxia system by MIPSO with other classical PSO algorithms. The experimental results show that the MIPSO algorithm is a successful and feasible approach for reactive power optimization.

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