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A New Variation Particle Swarm Optimization for Multi-objective Reactive Power Optimization

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Abstract: In order to overcome the particle swarm algorithm easy to fall into local optimal value and the lack of late slow convergence, this study presents a cloud model based on adaptive particle swarm optimization algorithm. The algorithm according to the fitness value of the particle populations of particles into the near optimal values closer to the optimal value and away from the optimal value of three subgroups and the generation of different populations to adopt a different strategy to generate inertia weight, where the normal cloud generator algorithm uses adaptive dynamic adjustment closer to the optimal particle subgroups of inertia weight, get rid of the shackles of algorithms into local optimum value; in the iteration algorithm uses the normal cloud to the mutation operation of the particle which makes the algorithm can quickly converge to the optimal solution. In summary presented Could Adaptive Variation Particle Swarm Optimization (CAVPSO) to solve the multi-objective optimization problem of reactive power. Use standard IEEE30 node system to test simulation results show that the use of CAVPSO algorithms to solve multi-objective optimization of reactive power superiority.

Key words: Multi-objective reactive power optimization, cloud model theory, particle swarm optimization algorithm, fuzzy logic

INTRODUCTION

Reactive power optimization of power system is the structure of the system parameters and load conditions under given conditions, in order to meet the system operation mode constraint as a precondition, through the optimization system control variables to maximize system voltage stability, improve voltage quality and reduce network losses (Liu *et al*., 2009). It has a non-linear, multi-objective, multi-constraint, containing both continuous variables and discrete variables and so on. Currently on the reactive power optimization in many ways, but the traditional classical algorithm has inevitable limitations, it can't deal with discrete variables (Li *et al*., 2008), with the development of artificial intelligence and computer technology, there have been many intelligent algorithms such as genetic algorithms (Lou *et al*., 2005), simulated annealing algorithm, immune algorithm (Xiong and Cheng 2006), particle swarm algorithm and has been successively introduced into the power system reactive power optimization problem and achieve better results, PSO (Kennedy and Eberhart, 1995) especially the most prominent research. PSO by Kennedy and Eberhart in 1995 proposed a stochastic optimization based on swarm intelligence algorithms, The advantage of this algorithm is easy to implement, easy to operate, with fewer parameters, however, the particles in the search for early convergence speed is too fast (Li *et al*., 2011), late in the search, but easy to fall into local optimum and the convergence speed is too slow which is the main drawback of the PSO algorithm (Zhao and Li, 2010).

The cloud model (Liu *et al*., 2005) theory and particle swarm combined, according to the normal cloud model of cloud droplets with randomness and stable tendency characteristics, it uses normal cloud generator (Li, 2000) which adaptively adjust the inertia weight, speed up its search capabilities. Thus forming a cloud adaptive variation particle swarm optimization and multi-objective of the power system reactive power optimization problem solving (Li *et al*., 2009).

MULTI-OBJECTIVE OPTIMIZATION MODEL OF REACTIVE POWER

Objective functions: With the rapid development of the power system, reactive power optimization techniques also proposed higher requirements, this study mainly consider three sub-goals. Namely the minimum active

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power loss, voltage deviation ΔU Min and static voltage stability margin ΔV Maximum reactive power optimization model as a multi-objective function. Detailed multi-objective optimization model of reactive power as follows:

$$\begin{cases} \min(P_{Loss}) = \sum_{i,j\in N_B} G_k[(T_k U_i)^2 + U_j^2 - 2T_k U_i U_j \cos\theta_{ij}] \\ \min(\Delta U) = \sum_{i=1}^{N_L} (\frac{U_i - U_i^*}{\Delta U_{i\max}})^2 \\ \min(\Delta V) = \min(1-\delta_{\min}) \end{cases} \quad (1)$$

in which: G_k is between nodes i and j, k branch conductance; N_B is a participation in active power loss calculation of the number of branches of the system; T_k is the transformer ratio k; θ_{ij} is a voltage phase angle difference; ΔU_{max} is the maximum permitted voltage deviation; N_L is the total number of load nodes.

Power flow constraints

Equality constraints:

$$\begin{cases} P_{gi} - P_{di} - U_i \sum_{j\in N_i} U_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0 \\ Q_{gi} + Q_{ci} - Q_{di} - U_i \sum_{j\in N_i} U_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) = 0 \end{cases} \quad (2)$$

Inequality constraints:

$$\begin{cases} U_{gi}^{\min} \le U_{gi} \le U_{gi}^{\max}, i\in N_g \\ T_k^{\min} \le T_k \le T_k^{\max}, k\in N_T \\ Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, i\in N_C \\ Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, i\in N_g \\ U_{Li}^{\min} \le U_{Li} \le U_{Li}^{\max}, i\in N_L \end{cases} \quad (3)$$

where, G_{ij}, B_{ij}, θ_{ij} respectively, between node i and j, the conductance, the susceptance and the phase angle difference; U_{gi}, T_k, Q_{ci} are the generator terminal voltage node, adjustable transformer tap and reactive power compensation node capacity; a, b, respectively, for the load node voltage and reactive power of the generator nodes; $U_{gi}^{\min}$, $U_{gi}^{\max}$, $T_k^{\min}$, $T_k^{\max}$, $Q_{ci}^{\min}$, $Q_{ci}^{\max}$, $U_{Li}^{\min}$, $U_{Li}^{\max}$, $Q_{gi}^{\min}$, $Q_{gi}^{\max}$, respectively, the corresponding variable upper and lower limits.

Reactive power optimization of multi-objective fuzzy solution: In this study, the above mentioned three sub-objective optimization of reactive power into the [0, 1] interval values of the membership function. For the Eq. 1 multi-objective mathematical model listed, have three sub-objective function corresponding membership functions are $\mu_1(x)$, $\mu_2(x)$, $\mu_3(x)$:

$$\begin{cases} \mu_1(P_{Loss}) = (P_{loss\max} - P_{loss})/(P_{loss\max} - P_{loss\min}) \\ \mu_2(\Delta U) = (\Delta U_{\max} - \Delta U)/(\Delta U_{\max} - \Delta U_{\min}) \\ \mu_3(\Delta V) = (\Delta V_{\max} - \Delta V)/(\Delta V_{\max} - \Delta V_{\min}) \end{cases} \quad (4)$$

According to cross-fuzzy decision, the original problem can be transformed into a single objective form, you can according to Eq. 5 for solving multi-objective reactive power optimization to get the optimal solution x*:, Where, μ_p (x_1, x_2) is the optimal membership degree.

$$x*: \max(\mu_p(x_1, x_2)) = \max\{\min(\mu_1(P_{loss}), \mu_2(\Delta U), \mu_3(\Delta V))\} \quad (5)$$

IMPROVED PSO

PSO algorithm: PSO algorithm of the foraging birds from research. Each particle in the PSO algorithm can be regarded as one of the solution in space. if the particle swarm size is M, the position of particle i can be expressed as a vector $X_i = (x_{i1}, x_{i2}, \dots, x_{ij}, \dots, x_{id})$, its speed can be expressed as a vector $v_i = (v_{i1}, v_{i2}, \dots, v_{id})$, its individual optimum value is $p_i = (p_{i1}, p_{i2}, \dots, p_{id})$, its global best value is $p_g = (p_{g1}, p_{g2}, \dots, p_{gd})$, particle i will update it is own pace and position according to the following equation:

$$\begin{aligned} & v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + \\ & c_2 r_2 (p_g(t) - x_i(t)) x_i(t+1) = x_i(t) + v_i(t+1) \end{aligned} \quad (6)$$

where, d is the dimension of solution space, namely, the number of variables: t is the evolutionary algebra, M is the population size. M is the inertia weight, r_1 and r_2 are Random Numbers distributed in [0, 1], c_1 and c_2 are constant, usually called learning factor. When the particles continuously adjust their position, they set the maximum speed as v_{max}, when V_i exceed the V_{max}, V_i is equal to V_{max}.

Cloud theory: The concept of cloud is an uncertainty transition model which translates one qualitative concept denoted by linguistic value into a quantitative one. Definition 1:Sets U as a quantitative discourse domain presented by determinate numerical values and sets $\tilde{A}$ as a qualitative concept in the domain U. If a quantitative value x belongs to U and x is a stochastic realization of the concept $\tilde{A}$ then an assured degree μ_A (X)$\in$[0, 1] of x to $\tilde{A}$ is a random number which has a determinate tendency:

$$\mu_A(x): U \to [0,1], \forall x \in U, x \to \mu\ (x) \quad (7)$$

Then, the distribution of x in domain U is defined as a cloud. Each x is called as one cloud drop.The cloud model is described by three number characteristics:

Expected value Ex, entropy En and hyper entropy He. As the distribution of μ_A (X) is the normal distribution, the cloud model is called as the normal cloud model.

Based on cloud model adaptive parti-cle swarm adjustment strategy: Set:

$$f_{avg} = \frac{1}{N}\sum_{i=1}^{N} f_i$$

is the average fitness value of PSO, Press the fitness value will be divided into three subgroups of the population that is close to the optimal particle populations closer to the optimal particle populations and away from the optimal particle, Where f_i is the particle X_i in the k-th iteration fitness value; Fitness value than the fitness value of f_{avg} averaged to obtain f'_{avg} Adaptation inferior averaging the values of f'_{avg} to obtain f''_{avg}. Each sub-populations using different inertia weight ω generation strategy, ω specific generation rules are as follows:

- f_i superior f'_{avg}

Fitness value of particles smaller than f'_{avg}, Such particles are already quite close to the global optimum particle so just to accelerate its global convergence speed, Let ω value of 0.4.

- f_i superior f''_{avg} and inferior f'_{avg}

Such particles are normal cloud generator using nonlinear dynamic adjustment of particle X_i inertia weight because such particles are particles in the ordinary population. Adaptive particle swarm algorithm to generate a new inertia weight as follows:

$$\begin{aligned} &E_x = f'_{avg} \\ &E_n = (f'_{avg} - f_{min})/c_1 \\ &H_e = E_n/c_2 \\ &E'_n = \mathrm{normrnd}(E_n, H_e) \\ &\omega = 0.9 - 0.5 * e^{\frac{-(f_i - E_x)^2}{2(E'_n)^2}} \end{aligned} \tag{8}$$

Wherein, c_1, c_2 for the control parameters, as:

$$0 < e^{\frac{-(f_i - E_x)^2}{2(E'_n)^2}} < 1$$

so ω∈[0.4, 0.9], Thus ω will be with the fitness value of particles is reduced thereby reducing the dynamic implementation of fitness smaller particles get smaller ω values.

- f_i inferior f''_{avg}

Meet the above criteria particles are particles of poor population that is far from the global optimum position, ω taking 0.9.

Adjust strategies of cloud mutation p-article swarm optimization algorithm: For particles in the presence of the late evolution of slow convergence and easy to fall into local minima and other issues, it's take on the part of the particle mutation operation. Cloud variation particle swarm optimization algorithm is based on each individual particle and the global extremum through normal cloud generator extreme expectations, entropy and hyper entropy to complete particle variation.

Through a one-dimensional normal cloud operators need to generate mutation particle swarm. according to the three parameters of the cloud model to the next generation population.

Solution of Reactive Power Optimization based on CAVPSO: Combined with the above, this study give the cloud adaptive variation particle swarm algorithm to solving multi-objective process. The main steps of solving the multi-objective optimization of Reactive Power Optimization are as follows:

- Initialization required parameters of algorithm, input trend data, set the control variable binding coverage, population size, maximum number of iterations, etc.
- Determine the sub-goals and constraints membership, to transformed multi-objective optimization model into a single objective optimization model according to blur solution in 1.3
- Flow calculation, get the current fitness value of each particle, determine the optimum value of the individual and the global, Determine whether the variance reach the threshold value N, If reach the threshold, then take mutation through the mutation strategy on the particle swarm, otherwise, go to Step 4)
- Each particle evolution operator based evolutionary strategy, Determine the speed and position of the new generation of X_i and Global optimum position of each particle and the individual optimal value and fitness value
- Determine whether the termination condition is satisfied, go to step 3) if not satisfied, otherwise, end of the iteration and output optimal solution

NUMERICAL EXAMPLES

This study selection IEEE 30-bus system as a test system simulation example, Matlab 7.0 preparation

Table 1: Average optimization results

IEEE30 node system	Active power loss/pu	Offset voltage/pu	Static voltage stability margin index	Lower loss rate (%)
Initial state	0.0551	0.0318	0.1295	-
PSO	0.0516	0.0172	0.1375	6.35
CAPSO	0.0496	0.0165	0.1479	9.98
CAVPSO	0.0490	0.0128	0.1652	11.07

Table 2: Average optimization results adding IA

IEEE30 Node System	Active Power Loss /pu	Offset Voltage /pu	Static voltage stability margin index	Lower loss rate /%
Initial state	0.0551	0.0318	0.1295	-
IA	0.0518	0.0191	0.1546	5.98
PSO	0.0516	0.0172	0.1375	6.35
CAVPSO	0.0490	0.0122	0.1792	11.07

Table 3: Values of control variable

Variables	No.	PSO	IA	CAPSO	CAVPSO
V1	1	1.0591	1.0501	1.0730	1.0768
V_2	2	1.0334	1.0315	1.0673	1.0681
V_5	5	1.0207	1.0160	1.0742	1.0352
V_8	8	1.0341	1.0193	1.0821	1.0451
V_{11}	11	1.0944	1.0352	1.0714	1.0622
V_{13}	13	1.0626	1.0331	1.0672	1.0710
T_1	6-9	0.9000	0.9651	0.9011	1.0100
T_2	6-10	0.9250	0.9750	1.1102	0.9900
T_3	4-12	0.9250	0.9500	0.9490	1.0000
T_4	28-27	0.9038	0.9146	0.9146	0.9600
Q_{10}	10	0.2000	0.2400	0.1084	0.2000
Q_{24}	24	0.2000	0.1200	0.0657	0.1200

CAVPSO applied using multi-objective reactive power optimization procedures and flow calculation procedures, the trend calculated using the Newton - Raphson method.

Experimental data are standard values, where the reference power is 100 MVA, regulating transformer ratio set in steps of 0.025, Adjust the ratio between 0.90~1.10 p.u. maximum and minimum number of stalls ±8, Compensation capacitor QC adjustable in steps of 0.04, Compensation to a maximum of 0.5 pu, initial voltage and transformer turns ratio of 1.0. Particle swarm size n = 40, Learning factor c1 = c2 = 2, ωmin = 0.4, ωmax = 0.9, maximum number of iterations Maxiter = 100, variance threshold N = 0.2.

Experiment 1: Under the same conditions, independently of the algorithms run 50 times, The Particle Swarm Optimization (PSO), cloud APSO (CAPSO) and the proposed cloud adaptive variation particle swarm optimization (CAVPSO) three algorithms to optimize the average optimal results were compared, comparing the results shown in Table 1.

Table 1 shows that the proposed algorithm CAVPSO is applied to multi-objective reactive power optimization calculation, Active power loss by the 5.51 MW down 4.90 MW, a decline of 11.07 percent, The result is better than the other two algorithms. In addition, the other two sub-objective function values also have obvious advantages.

Experiment 2: Under the same basic conditions, then optimization of the results of Experiment 1 with the Immune Algorithm (IA) for comparative experiment, the optimization algorithm of the average optimal results as Table 2.

Table 2 shows, the Immune Algorithm (IA) for multi-objective optimization results compared with the average standard particle swarm optimization results, Among them, the active power loss and voltage offset inferior PSO algorithm, however, the static voltage stability margin index is superior to PSO and CAVPSO algorithms are superior to each sub-goal above two algorithms to verify the proposed algorithm is effective and feasible.

Table 3 gives the IEEE 30 node system after optimization of the four algorithms optimal value of the control variable.

Table 3 shows, CAVPSO algorithm optimized for all node voltages, the control variable from its upper and lower limit values ??have a certain distance, solves the reactive power output close to the limit, you can solve reactive power optimization objective function and the conflict between system voltage safety problem. According to the above comparison shows that the proposed method for multi-objective optimization of reactive power optimization can get high-quality solution.

CONCLUSION

We propose a new method to improve the particle swarm algorithm using cloud model. The improved algorithm is applied to IEEE30 bus system to solve the multi-objective reactive power optimization operation, The results show that the proposed algorithm effectively solve the PSO precocious problem.

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