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Cloud Particle Swarm Algorithm Improvement and Application in Reactive Power Optimization

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Abstract

To resolve the problems that cloud particle swarm optimization (CPSO) was easily trapped in local minimum and possessed slow convergence speed and early-maturing during distribution grid reactive power optimization, CPSO algorithm was improved based on cloud digital features in this paper. The method combined Local search with global search together based on solution space transform, where the crossover and mutation operation of the particles were implemented based on normal cloud operator. And thus, the defects of CPSO algorithm were better tackled. Finally, applied in bus IEEE30 system, the simulation results show that the better global solution is attained using the improved CPSO algorithm, and its convergence speed and accuracy possesses a dramatic improvement.

Keywords: *cloud particle swarm, Improvement, distribution grid, reactive power optimization*

1. Introduction

Reactive power optimization is a multi-constraint, large-scale and nonlinear combinatorial optimization problem in power systems. It is a reactive regulatory method to acquire one or more system optimization aims through the control of some variables under all the constraints when the system parameters and the loads are given beforehand [1]-[3]. The means to resolve the problems include conventionally classical algorithm and artificial intelligence methods. The classical algorithms include linear regulation method, and non linear regulation, and as well as mixed integer programming and so on, whose main problems are the disposal of discrete variables and multi-extremum searching. In process of optimization the general puzzles such as dimensionality curse and larger calculation error exists, as a result, the ideal optimization aims are hard to be acquired [4]-[6]. And artificial intelligence methods such as simulated annealing, genetic algorithm, immune algorithm, ant colony algorithm, particle swarm optimization, and neural network have been widely applied to resolve power systems reactive power optimization [7]-[9]. These algorithms with swarm intelligence based have better global searching ability and process the discrete multi-objective optimization problems. However, single algorithm generates many defects like local extremum and slow convergence speed so that the desired results is difficult to be achieved. In resent years, some new reactive power optimization methods, such as dynamic adaptive differential evolution algorithm and improved particle swarm optimization algorithm, are proposed in [10-11], respectively, where the selection of weight and convergence precision are still not too accurate. Based on it, according to the descriptions on cloud model that it embodies the basic principles of species evolution in nature, i.e., certainty is contained in uncertainty, and stability is attached to variation in knowledge representation, cloud particle swarm optimization(CPSO) based on cloud digital features (Ex, En, He) is investigated and applied, the results indicate CPSO has better stability and randomness [12-13]. To aim at the flaws of conventional PSO that the inertia weight generating mechanism can not reflect the practical seeking process, CPSO divides the whole population into three subpopulations, and diverse generating strategies of inertia weights are applied. CPSO whose the modulation strategies of inertia weights adopt the X condition cloud generator is defined as self-adaptive CPSO. But self-adaptive CPSO also expose some shortcomings in power systems reactive power optimization such as easy trapping in a local minimum, and early mature and poor convergence precision, and etc, it is expected to improved, further [14-15].

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Hence, in this paper CPSO algorithm is improved from the two facets and applied in bus IEEE30 system, which is defined as ICPSO algorithm, the excellent results are achieved and indicate that the convergence speed and accuracy of reactive power optimization for distribution grid are well solved.

2. The Proposed Algorithm

2.1. Basic CPSO Algorithm

To aim at the defect of basic PSO algorithm that the strategy to decrease progressively of inertia weight can not reflect the practical searching process, CPSO makes the improvements on it, i.e., it will divide the particles into the three subpopulations during evolution, and diverse updating strategies of inertia weights are applied, the model is described below.

$$v_{id}^{(t+1)} = \omega v_{id}^{(t)} + c_1 r_1 (P_{id} - x_{id}^{(t)}) + c_2 r_2 (P_{gd} - x_{id}^{(t)}) \tag{1}$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)} \tag{2}$$

$$\omega = 0.9 \sim 0.5 * e^{\frac{-(fi-Ex)^2}{2(En')^2}} \tag{3}$$

where Eq.1 is the speed updating formula, Eq.2 is displacement updating formula, and Eq.3 is updating formula of inertia weight. V_{id} is the flying speed of the *i*th particle in *D*-dimensional space, and x_{id} is the displacement of the *i*th particle in *D*-dimensional space, and ω is the updating formula of inertia weigh. In (1) to (3), parameter *t* expresses the iteration times, and c_1 and c_2 are non-negative learning factors in range of 1 to 2, and $r_1$and r_2 are random variables with a scope of zero to one, P_{id} is the optimal position sought by the ith particle so far today, and Pgd is the optimal position sought by the whole particle until now, fi is the fitness value of the ith particle, E_x is the desired value and E_n is the entropy of cloud drops.

In CPSO algorithm, the particles are divided into the three subpopulations according to their fitness values in each iteration process, and they evolve according to diverse evolution strategies. Let the colony scale of the particle be *N*, and then the average fitness value of the particles can be expressed by

$$f_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} f_i \tag{4}$$

Let $f_{\text{avg}}^{'}$ be the average fitness value of the particles whose fitness values are larger than f_{avg}, and $f_{\text{avg}}^{''}$ be the average fitness value of the particles whose fitness values are lower than f_{avg}, and the fitness value of the most optimal particle is expressed using $f_{\min}$. In concrete iteration process, the inertia weight updates according to (3) but diverse evolution strategies are applied. If f_i is better than $f_{\text{avg}}^{'}$, then the evolution strategy is adopted according to (1), but the second item in the right side in (1), i.e., cognitive model, is abandoned. This means the particle evolves according to social model alone so as to accelerate the global convergence. And conversely, if f_i is worse than $f_{\text{avg}}^{''}$, then the evolution strategy is adopted according to (1), but the third item in the right side in (1), i.e., social model, is ignored. This means the particle evolves according to cognitive model alone to accelerate the convergence speed of the particles that they possess poor performance. Finally, if $f'_{\text{avg}} < f_i < f''_{\text{avg}}$, then the evolution strategy of the particles adopts the full model like (1).

2.2. Improved CPSO Algorithm

As previously mentioned, CPSO still exposes some deficiencies during application, and expects to be improved. Hence, we make the following improvements for CPSO using cloud digital features (Ex, En, He) to encode.

1) With the aim of population alternative and solution space transform, the global search and local search are combined.

The majority of the operating time is consumed in population updating in basic CPSO algorithm, and moreover, in the evolution later period, the convergence speed is often more slow, and so population alternative and solution space change are introduced.

The main thinking of population alternative is that the whole particle swarm is divided into several subpopulations, one of which is defined as main population, and other ones is defined as auxiliary populations, they seek the optimizing aim in solution space applying different seeking means. During seeking process, the parts of main population and auxiliary populations are exchanged to ensure the diversity of the particles in main population under some conditions. In this way, the early mature can be avoided for main colony to guarantee the global extremum to be found.

In CPSO, the traversal space is [-1, 1] of every dimension of the particles. For correctly evaluating the superiority-inferiority of the cloud particles in current position, the solution space transform is required, that is, from unit space $I=[-1, 1]^n$ to optimization solution space mapping. Let the ith cloud operator of the particle P_j be $[\alpha_i^j, \beta_i^j]^n$, and so corresponding solution space variables are described by

$$X_{ic}^j = \frac{1}{2}[b_i(1+\alpha_i^j) + a_i(1-\alpha_i^j)]$$
$$X_{i\delta}^j = \frac{1}{2}[b_i(1+\beta_i^j) + a_i(1-\beta_i^j)] \tag{5}$$

And then the optimization is made in the solution space. If the optimal value is better than the current best solution, and replace it using the optimal value.

2) To realize the crossover and mutation operation of the particles according to normal clouds operator so as to improve the seeking fashion of the algorithm.

Crossover and mutation probabilities are described as follows.

$$Ex = \bar{f} = \frac{F_{\mathrm{f}}}{F_{\mathrm{f}} + F_{\mathrm{m}}} x_f + \frac{F_{\mathrm{m}}}{F_{\mathrm{f}} + F_{\mathrm{m}}} x_{\mathrm{m}}$$
$$En = (f_{\max} - \bar{f}) / c_1$$
$$He = En / c_2 \tag{6}$$
$$En' = RANDN(En, He)$$
$$p_c = \begin{cases} k_1 e^{\frac{-(f' - Ex)^2}{2(En')^2}} & f' \geq \bar{f} \\ k_3 & f' < \bar{f} \end{cases}$$

where x_f and x_m respectively express father individual, mother individual, F_f and F_m respectively express father individual fitness and mother individual fitness, c_1 and c_2 are control variables, $\bar{f}$ is average fitness.

Definition 1(*mutation*): To give out the threshold *N* and *K* beforehand, when the global extremum does not change, or whose change range less than *K* in continuous *N* times iterations during evolution process, at the moment, the particles are considered to get into the local extremum, according to global extremum, all the particles are implemented mutation operation through the normal clouds generator [12].

Definition 2: 1-dimensional normal clouds operator, defined as $Ar^{\mathrm{Forward}}C(Ex, En, He)$, is a mapping of the whole characteristic from qualitative expression to quantitative expression, i.e., π: C→Π, and the following conditions require to be met.

$$\Theta = \{t_i \mid Norm(En, He),\ i = 1 \ldots N\};$$
$$X = \{x_i \mid Norm(Ex,\ t_i),\ t_i \in \Theta,\ i = 1 \ldots N\}; \tag{7}$$
$$\Pi = \{(x_i, y_i) \mid x_i \in X, t_i \in \Theta, y_i = \exp(-(x_i - Ex)^2 / (2t_i^2))\}.$$

where Norm is the normal random variable function, and t_i is cloud drop, N is the number of cloud drop. According to (7), the qualitative concept C(*Ex*, *En*, *He*) is conversed as a cloud drop set expressed by numerical values, and that realizes the transformation from concept space to numerical space. Obviously, 1-dimensional normal cloud operator may expand into *n*-dimension.

During CPSO evolution, some cases often appear such as no contemporary optimal solution, and that the more evolutionary deviates from the optimal solution. To change the status, the following improvements are required.

As the colony initialization, the initial value is recorded on the current position and velocity of each particle, and then, the fitness of each particle is calculated, and judge whether it reaches mutation thresholds. If the conditions are met, according definition 1 each particle is implemented mutation operation, and otherwise according to (1) and (2) each particle is carried out updating operation. After the end of each generation, the optimal solution is selected from the three subpopulations, and defined as the global optimal solution. If the optimal solution meets the fitness requirements, or iteration times arrive at the set times, the evolution process terminates.

For the improved algorithm, the parameters *Ex*, *En*, *He*, *K*, and *N* , and as well as the inertia weight ω and accelerating factors C_1 and C_2 , have very important influences on the algorithm properties. Obviously, these improvement measures not only enhance the diversity of the colony, but also improve the ability to search optimization, and reflect the ability of normal cloud operator to operate the particles.

3. Research Method

3.1. Reactive Power Optimization Model Description

Under the condition of power systems reactive power balance, power systems reactive power optimization takes the generator bus voltages, and the transformation ratio of transformer on-load voltage regulating, and compensation capacitor as control variables, and reduces the grid loss and improves the quality of power voltage as the aim. In this paper, from consideration of economic aspect, active grid loss minimum is selected as the optimizing aim, and then, the aim function is described as follows[16]

$$\min F = \sum_{i=1}^{L} P_{\text{loss}} + \lambda_{\text{V}} \sum_{i=1}^{M} \left(\frac{\Delta U_i}{U_{i\max} - U_{i\min}} \right)^2 + \lambda_{\text{G}} \sum_{i=1}^{N} \left(\frac{\Delta Q_{Gi}}{Q_{Gi\max} - Q_{Gi\min}} \right)^2 \tag{8}$$

where ΔU_i and ΔQ_{Gi} are expressed by

$$\Delta U_i = \begin{cases} U_{i\min} - U_i \ , & U_i < U_{i\min} \\ 0 \ , & U_{i\min} \le U_i \le U_{i\max} \\ U_i - U_{i\max} \ , & U_{i\max} < U_i \end{cases}$$

$$\Delta Q_{Gi} = \begin{cases} Q_{Gi\min} - Q_{Gi} & Q_{Gi} < Q_{Gi\min} \\ 0 & Q_{Gi\min} \le Q_{Gi} \le Q_{Gi\max} \\ Q_{Gi} - Q_{Gi\max} & Q_{Gi\max} < Q_{Gi} \end{cases}$$

And the constraints of the variables are expressed by

$$\begin{cases} Q_{Gi\min} \le Q_{Gi} \le Q_{Gi\max} & i = 1,2,\cdots,n_{\text{G}} \\ U_{i\min} \le U_i \le U_{i\max} & i = 1,2,\cdots,n_M \end{cases}$$

$$\begin{cases} Q_{ci\min} \le Q_{ci} \le Q_{ci\max} & i = 1,2,\cdots,n_c \\ T_{i\min} \le T_i \le T_{i\max} & i = 1,2,\cdots,n_{\text{T}} \\ U_{Gi\min} \le U_{Gi} \le U_{Gi\max} & i = 1,2,\cdots,n_{\text{G}} \end{cases}$$

And the power constraints are represented by

$$\begin{cases} P_{Gi}-P_{Li}=U_i\sum_{j=1}^{n}U_j(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij})=0, & i=1,2,\cdots,n, \quad i\neq j. \\ Q_{Gi}+Q_{Ci}-Q_{Li}=U_i\sum_{j=1}^{n}U_j(G_{ij}\sin\delta_{ij}+B_{ij}\cos\delta_{ij})=0, & i=1,2,\cdots,n_{\mathrm{PQ}}. \end{cases}$$

where the implication of each variable are presented below.
N: Generator nodes total number.
M: Load nodes total number.
L: Grid circuit number.
P_{loss}: Power systems grid loss.
U_i, $U_{i\max}$, $U_{i\min}$: Node voltage, voltage limitation.
Q_{Gi}, $Q_{Gi\max}$, $Q_{Gi\min}$: Generator reactive power, reactive power limit.
λ_{v}, λ_{G}: Cross-border penalty coefficients.
Q_{Ci}: Compensation capacitor capacity.
U_{Gi}: Generator terminal voltage.
T_i: Adjustable transformer.
P_{Gi}: Generator active power.
G_{ij}: Mutual conductance between node i and node j.
B_{ij}: Mutual susceptance between bus i and j.
δ_{ij}: Voltage phase difference between node i and j.
n_{PQ}: PQ node number.
P_{Li}, Q_{Li}: Load nodes active power and reactive power.

3.2. Distribution Grid Reactive Power Optimization Method Using Improved CPSO

In CPSO algorithm, the could drops are generated using X conditions cloud generators, that is cloud drop expressed by drop(x0, μi) as the particles, the displacements of the particles in solution space corresponds to control variables in power system reactive power optimization, such as terminal voltage U_{G} of the generator, parallel capacitor capability Q_{C}, and the transform ratio T_{K} of transformer on load voltage regulating, the number of dimensions of each particle is equal to the number of the control variables, that is,

$$x_i=\left[U_{G1},\cdots,U_{GN_G},Q_{C1,}\cdots,Q_{CN_C},T_{K1},\cdots,T_{KN_K}\right]^T \tag{9}$$

where N_{G}, N_{C}, and N_{K} respectively express the number of the generators, capacitors, and transformers.

Power system reactive power optimization is implemented based on the improved CPSO proposed in this paper, whose code adopts real number with continuous and discrete variables mixed. The whole step is described below.

1)To input the initial parameters, including power systems parameters, control variables, and constraint conditions. To set the scale of the colony, and initialize the population, which includes the displacement Xi, the individual extremum Pbest, and the global extremum Gbest of each particle, and so on.

2) For each particle in colony, tide current and grid loss calculation are implemented, according to (8) the fitness value of which is evaluated, and Pbest, and Gbest are updated.

3) To judge whether the mutation threshold conditions are arrived at, if the conditions hold, then mutation operation is implemented according to define 1. Let Ex= Gbest, En= 2Gbest, He= En /10, then according to define 2 mutation operation is completed. Those particles which can not reach mutation thresholds turn to the fouth step directly.

4) To perform evolution operator for each particle. Let Ex= Pbest, En= 2Pbest, He= En /10, according to define 2 a new particle j is generated, and let i=j, thus evolution operation is completed.

5) If iteration times arrive at the maximum times, then output the Gbest, and the optimization process ends. Otherwise turn to the 2nd step.

5. Results and Discussion

To verify the effectiveness of the proposed method, we take bus IEEE30 system as an example to illustrate. IEEE30 bus system, as shown in Figure 1, contains 41 lines, 22 load nodes, and 6 generator nodes, where the node 1, 2, 5, 8, 11, 13 is the generator nodes, and 1 is balance node, the rest for PV nodes, 10 and 24 is reactive power compensation nodes. The adjusting step-length of the capacitor 10 is 0.1, the one of the node 24 is 0.02, and the maximum tap positions of the two are five-position. Subcircuits including 6-9, 6-10, 4-12, and 27-28 are transformer branches, the scope of the transformer transform ratios are $\pm 8\times 1.25\%$. The upper and lower limitation of the reactive power and voltage level of the generator can be found in Tab.1. Benchmark power is set as SB = 100 MVA.

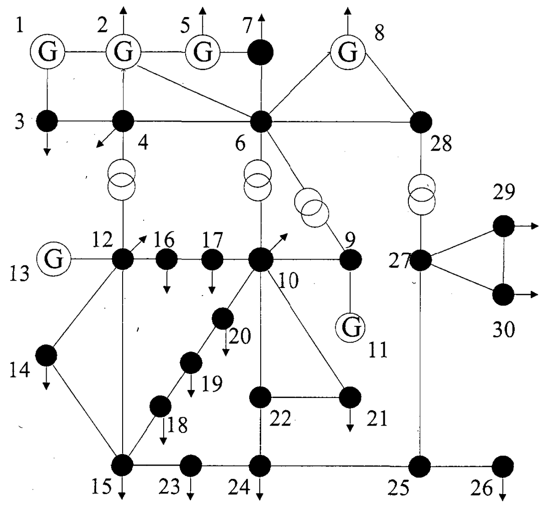

Figure 1. IEEE 30 node bus system

Table 1. Active power limits of PV nodes and upper and low limits of reactive power generation of PV nodes and the balance node

Node number	PG	$Q_{G\max}$/pu	$Q_{G\min}$/pu	$U_{G\max}$/pu	$U_{G\min}$/pu
1	——	0.596	-0.298	1.1	0.9
2	0.8	0.48	-0.24	1.1	0.9
5	0.5	0.6	-0.3	1.1	0.9
8	0.2	0.53	-0.265	1.1	0.9
11	0.2	0.15	-0.075	1.1	0.9
13	0.2	0.155	-0.0775	1.1	0.9

In the same initial conditions, i.e., the size of the population is set as 100, and mutation threshold N is set by 2, and the maximum iteration times is given by 500, and the adjustment of the inertia weight is based on (4), ICPSO is compared with CPSO and PSO algorithms. Table 2 shows the compared results of the three for IEEE 30-node system which are the average values of the optimal values after 50-times optimization.

Table 2. Comparison of the optimal results for different algorithms in bus IEEE30 system

Algorithm	Power loss(pu)	Grid loss rate falling (%)	Qualified rate of the voltage (%)
PSO	0.0608	21.01	90
CPSO	0.0591	23.21	100
ICPSO	0.0573	25.16	100

Under the initial states, the terminal voltages of all the generators and the transformer-ratio of all the transformers are 1.0, the system total active power grid loss is 0.0771. Seen from Table 2, using ICPSO method, after the reactive power optimization, the system total power loss reduces to 0.0573, and grid loss rate lessens 25.16%. Clearly, this result is better than the ones of the PSO and CPSO. Hence, ICPSO algorithm is a more effective method. It can acquire the global optimal solution more possible than PSO and CPSO, and the voltage amplitude of each node and the scope of each generator reactive power are not out of limits. The optimized control variables are shown in Table 3.

Table 3. Values of control variables after optimization

Control variable	Nodes number	Voltage /pu	Control variable	Nodes number	Tap position
V_1	1	1.0733	T_1	4-12	6.0000
V_2	2	1.0703	T_2	6-9	3.0000
V_5	5	1.0409	T_3	6-10	1.0000
V_8	8	1.0490	T_4	27-28	1.0000
V_{11}	11	1.0666	Q_{10}	10	2.0000
V_{13}	13	1.0727	Q_{24}	24	3.0000

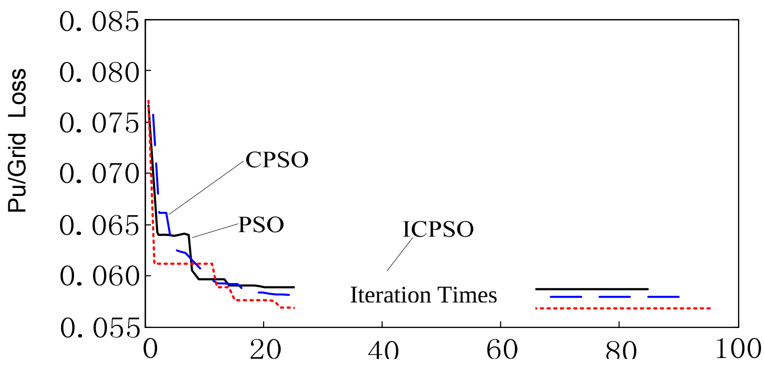

Figure 2. Convergence curves of PSO, CPSO and ICPSO algorithms

Figure 2 shows the convergence curves of the three algorithms. Seen from Figure 2, there is a fast falling before 12 times in CPSO convergence curve, but hereafter the curve drops very slowly, and the final convergence effect is not ideal. PSO curve has a fast falling at the initial term, but at later stage, the curve falls into standstill state due to the early-maturing of the particles. ICPSO curve descends very fast at the very start, and then is followed by a buffer stage between 3 and 12 interation times, hereafter drops slowly and arrives at the optimal value at around 23 times.

6. Conclusion

The ICPSO proposed in this paper fully makes use of randomness and stability characteristics of the cloud drop to realize the combination of the global and local seeking based on solution space transformation technology, and also realize the crossover and mutation operations using normal cloud operator. By applying in IEEE30 bus system, the simulation results prove that the improved CPSO algorithm possesses dramatic improvement in seeking-optimization speed and precision, and computation efficiency and convergence stability are better.

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