

Reduction of Active Power Loss by Using Adaptive Cat Swarm Optimization

K Lenin, B Ravindhranath Reddy

Jawaharlal Nehru Technological University Kukatpally,
Hyderabad 500 085, India
email: gklenin@gmail.com

Abstract

This paper presents, an Adaptive Cat Swarm Optimization (ACSO) for solving reactive power dispatch problem. Cat Swarm Optimization (CSO) is one of the new-fangled swarm intelligence algorithms for finding the most excellent global solution. Because of complication, sometimes conventional CSO takes a lengthy time to converge and cannot attain the precise solution. For solving reactive power dispatch problem and to improve the convergence accuracy level, we propose a new adaptive CSO namely 'Adaptive Cat Swarm Optimization' (ACSO). First, we take account of a new-fangled adaptive inertia weight to velocity equation and then employ an adaptive acceleration coefficient. Second, by utilizing the information of two previous or next dimensions and applying a new-fangled factor, we attain to a new position update equation composing the average of position and velocity information. The projected ACSO has been tested on standard IEEE 57 bus test system and simulation results shows clearly about the high-quality performance of the planned algorithm in tumbling the real power loss.

Keywords: Optimal Reactive Power, Transmission loss, Adaptive cat swarm optimization

1. Introduction

Optimal reactive power dispatch (ORPD) problem is multi-objective optimization problems that reduce the real power loss. Various mathematical techniques like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the difficulty in managing inequality constraints. If linear programming is applied then the input-output function has to be articulated as a set of linear functions which mostly lead to loss of accurateness. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Global optimization has received widespread research awareness, and a great number of methods have been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9,10]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20], presents a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. Cat Swarm Optimization (CSO) which mimics the behaviour of cats [21]. By imitate the behaviour of cats and modelling into two modes, CSO can decipher the optimization problems. So in this paper, we plan an Adaptive CSO in order to attain the elevated convergence accuracy in a lesser amount of iteration. First we employ an adaptive inertia weight and adaptive acceleration coefficient. So, the new velocity update equation will be calculated in an adaptive formula. Then, our aim is to consider the effect of previous or next steps in order to compute the current position. So by

utilizing a factor namely 'Forgetting Factor', information values of steps will be dissimilar. Finally, we use an average form of position update equation composing new velocity and position information. The proposed algorithm ACSO been evaluated in standard IEEE 57 bus test system & the simulation results shows that our proposed approach outperforms all reported algorithms in minimization of real power loss.

2. Problem Formulation

The OPF problem is measured as a general minimization problem with constraints, and can be mathematically written in the following form:

$$\text{Minimize } f(x, u) \quad (1)$$

$$\text{Subject to } g(x, u) = 0 \quad (2)$$

and

$$h(x, u) \leq 0 \quad (3)$$

Where $f(x, u)$ is the objective function. $g(x, u)$ and $h(x, u)$ are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = (P_{g1}, \theta_2, \dots, \theta_N, V_{L1}, \dots, V_{LNL}, Q_{g1}, \dots, Q_{gng})^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = (V_g, T, Q_c)^T \quad (5)$$

or

$$u = (V_{g1}, \dots, V_{gng}, T_1, \dots, T_{Nt}, Q_{c1}, \dots, Q_{cNc})^T \quad (6)$$

Where N_g , N_t and N_c are the number of generators, number of tap transformers and the number of shunt compensators respectively.

3. Objective Function

Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in N_{br}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (7)$$

or

$$F = PL = \sum_{i \in N_g} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{N_g} P_{gi} - P_d \quad (8)$$

Where g_k : is the conductance of branch between nodes i and j , N_{br} : is the total number of transmission lines in power systems. P_d : is the total active power demand, P_{gi} : is the generator active power of unit i , and P_{gslack} : is the generator active power of slack bus.

Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v : is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{N_{pq}} |V_i - 1| \quad (10)$$

Equality Constraint

The equality constraint $g(x,u)$ of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (11)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

Inequality Constraints

The inequality constraints $h(x,u)$ reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{\min} \leq P_{gslack} \leq P_{gslack}^{\max} \quad (12)$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{\min} \leq V_i \leq V_i^{\max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_C \quad (16)$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

4. Cat Swarm Optimization

Cat Swarm Optimization is a new-fangled optimization algorithm in the field of swarm intelligence. The CSO algorithm replica the behaviour of cats into two modes: 'Search mode' and 'Trace mode'. Swarm is made of primary population composed of particles to explore in the solution space. Here in CSO, we employ cats as particles for solving the problem. In CSO, each cat has its own location composed of D dimensions, velocities for every dimension, a fitness value, which represents the accommodation of the cat to the fitness function, and a flag to identify whether the cat is in search mode or trace mode. The final solution would be the most excellent position of one of the cats. The CSO keeps the best solution until it reaches the end of the iterations [22].

Search mode

For modelling the behaviour of cats in resting time and being-alert, we use the search mode. In this mode is a time for opinion and deciding about next move. This mode has four main parameters which are mentioned as follow: search memory pools (SMP), search range of the selected dimension (SRD), calculate of dimension to change (CDC) and self-position consideration (SPC).

The process of search mode is describes as follow:

Step 1: create j copies of the present location of cat_k , where $j = SMP$. If the value of SPC is true, let $j = (SMP-1)$, then preserve the present location as one of the candidates.

Step 2: For every copy, according to CDC, arbitrarily Add or Subtract SRD percent the present values and reinstate the old ones.

Step 3: compute the fitness values (FS) of all candidate points.

Step 4: If all FS are not exactly equal, compute the selecting probability of every candidate point by (1), or else set all the selecting probability of every candidate point is 1.

Step 5: arbitrarily choose the point to move to from the candidate points, and replace the location of cat_k .

$$P_i = \frac{|SSE_i - SSE_{max}|}{SSE_{max} - SSE_{min}} \quad (17)$$

If the objective of the fitness function is to discover the minimum solution, $FS_b = FS_{max}$, otherwise $FS_b = FS_{min}$

Trace Mode

Trace mode is the second mode of algorithm. In this mode, cats craving to trace targets and foods. The procedure of trace mode can be described as follow:

Step 1: renew the velocities for each dimension according to (18).

Step 2: verify if the velocities are in the range of maximum velocity. In case the new velocity is over-range, it is set equal to the limit.

$$V_{k,d} = V_{k,d} + r_1 c_1 (X_{best,d} - X_{k,d}) \quad (18)$$

Step 3: renew the location of cat_k according to equation (19)

$$X_{k,d} = X_{k,d} + V_{k,d} \quad (19)$$

$X_{best,d}$ is the position of the cat, who has the best fitness value, $X_{k,d}$ is the position of cat_k , c_1 is an acceleration coefficient for extending the velocity of the cat to move in the solution space and usually is equal to 2.03 and r_1 is a random value uniformly generated in the range of [0,1].

Key explanation of CSO

In order to merge the two modes into the algorithm, we define a mixture ratio (MR) which specifies the rate of mixing of search mode and trace mode. This parameter makes a decision how many cats will be moved into search mode procedure. First of all, we generate N cats and initialize the positions, velocities and the flags for cats. (*) According to the fitness function, calculate the fitness value of the each cat and keep the best cat into memory (X_{best}). In next step, according to cat's flag, apply cat to the search mode or trace mode procedure. After finishing the associated progression, re-pick the number of cats and set them into search mode or trace mode according to MR parameter. At the end, check the termination condition, if satisfied, stop the program, and otherwise go to (*) [23].

5. Adaptive Cat Swarm Optimization

The trace mode of CSO has two equations: velocity update equation and position update equation. For attainment an adaptive CSO, we modify some of the parameters in velocity equation. Also to calculate the current location of cats, we deem the information of previous and next dimensions by using an extraordinary factor and then we attain a fresh

dynamic position update equation. We explain the proposed algorithm in two parts.

By means of Adaptive Parameters

In the proposed algorithm, we insert an adaptive inertia weight to the velocity equation which is updated in every dimension. By utilizing this parameter, we create equilibrium between global and local search ability. A large inertia weight make easy of a global search while a small inertia weigh make easy of a local search. First we employ a large value and it will be reduced gradually to the least value by using (20).

$$W(i) = W_s + \frac{i_{\max} - i}{2 \times i_{\max}} \quad (20)$$

Equation (20) specifies that the inertia weight will be renewed adaptively, where W_s is the starting weight, i_{\max} is the maximum dimension of benchmark and i is the existing dimension. So the maximum inertia weight happens in the primary dimension of the each iteration and it will be updated decreasingly in each dimension. In the projected algorithm W_s is equal to 0.5. Also, c_1 is an acceleration coefficient for extending the velocity of the cat to shift in the solution space. This parameter is a constant value and is usually equal to 2.03, but we use an adaptive formula to update it by (21).

$$C(i) = C_s + \frac{i_{\max} - i}{2 \times i_{\max}} \quad (21)$$

Equation (21) reveals that the adaptive acceleration coefficient will be steadily increased in each dimension and the greatest value happens in the last dimension. Here C_s is equal to 2.03.

By using these two adaptive parameters, we modify the velocity update equation for each cat to a new form describing in (22).

$$V_{k,d} = W(d) \times V_{k,d} + r_1 \times C(d) \times (X_{\text{best},d} - X_{k,d}) \quad (22)$$

Fresh Dynamic location Update Equation

In this part, we modify the location update equation to a new form. In the conventional CSO, the position of cat is including of current information of velocity and position. Occasionally in many cases, using of previous information in order to guess the current position is useful. Also, taking the advantages of next information can be suitable information for renewing the cat's position. So we use the two previous or next dimensions information of velocity and position by applying a fresh factor which is called 'Forgetting factor'. By this factor, the values of previous and next steps will be different. So the information value for first previous or next step is senior than second previous or next step. It means that the pressure of previous or next step is more significant than previous or next second step. New-fangled position update equation is described by (23). In the projected algorithm, γ is the forgetting factor and is equal to 0.8 (It is necessary to use $\gamma > 0.5$). This fresh position update equation is composing two new vibrant terms, average location information and average velocity information. Here, we employ the current and the average information of first and second previous or next dimensions for both velocity and position by applying a forgetting factor (γ).

$$X_{k,d} = \frac{1}{2} [\text{location inofrmation} + \text{velocity information}]$$

$$\text{location information} = X_{k,d} + \frac{(\gamma \times X_{k,d+1}) + (1-\gamma) \times (X_{k,d+2})}{2} + \frac{(\gamma \times X_{k,d-1}) + (1-\gamma) \times (X_{k,d-2})}{2}$$

$$\text{velocity information} = V_{k,d} + \frac{(\gamma \times V_{k,d+1}) + (1-\gamma) \times (V_{k,d+2})}{2} + \frac{(\gamma \times V_{k,d-1}) + (1-\gamma) \times (V_{k,d-2})}{2} \quad (23)$$

6. Simulation Results

The proposed ACSO algorithm for solving ORPD problem is tested for standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, seven generator-buses and 17 branches under load tap setting transformer branches. The possible reactive

power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table 1. The initial conditions for the IEEE-57 bus power system are given as follows:

$P_{load} = 12.221$ p.u. $Q_{load} = 3.251$ p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G = 12.6259$ p.u. $\sum Q_G = 3.3369$ p.u.

$P_{loss} = 0.26493$ p.u. $Q_{loss} = -1.2209$ p.u.

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after ACSO based optimization which are within their acceptable limits. In Table 3, a comparison of optimum results obtained from proposed ACSO with other optimization techniques for ORPD mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed ACSO approach for providing better optimal solution in case of IEEE-57 bus system.

Table 1. Variables limits for ieee-57 bus power system (p.u.)

reactive power generation limits							
bus no	1	2	3	6	8	9	12
Q_{gmin}	-1.2	-0.13	-0.03	-0.06	-1.2	-0.02	-0.3
q_{gmax}	2	0.6	0.5	0.23	2	0.03	1.43
voltage and tap setting limits							
V_{gmin}	V_{gmax}	V_{pqmin}	V_{pqmax}	t_{kmin}	t_{kmax}		
0.8	1.0	0.93	1.06	0.6	1.2		
shunt capacitor limits							
bus no	18		25		53		
q_{cmin}	0		0		0		
q_{cmax}	10		5.3		6.2		

Table 2. Control variables obtained after optimization by ACSO method for ieee-57 bus system (p.u.)

Control Variables	ACSO
V1	1.1
V2	1.078
V3	1.064
V6	1.057
V8	1.078
V9	1.044
V12	1.058
Qc18	0.0835
Qc25	0.326
Qc53	0.0615
T4-18	1.017
T21-20	1.068
T24-25	0.968
T24-26	0.936
T7-29	1.095
T34-32	0.948
T11-41	1.016
T15-45	1.068
T14-46	0.936
T10-51	1.044
T13-49	1.065
T11-43	0.913
T40-56	0.906
T39-57	0.968
T9-55	0.988

Table 3. comparative optimization results for ieee-57 bus power system (p.u.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [24]	0.25902	0.30854	0.27858
2	CGA [24]	0.25244	0.27507	0.26293
3	AGA [24]	0.24564	0.26671	0.25127
4	PSO-w [24]	0.24270	0.26152	0.24725
5	PSO-cf [24]	0.24280	0.26032	0.24698
6	CLPSO [24]	0.24515	0.24780	0.24673
7	SPSO-07 [24]	0.24430	0.25457	0.24752
8	L-DE [24]	0.27812	0.41909	0.33177
9	L-SACP-DE [24]	0.27915	0.36978	0.31032
10	L-SaDE [24]	0.24267	0.24391	0.24311
11	SOA [24]	0.24265	0.24280	0.24270
12	LM [25]	0.2484	0.2922	0.2641
13	MBEP1 [25]	0.2474	0.2848	0.2643
14	MBEP2 [25]	0.2482	0.283	0.2592
15	BES100 [25]	0.2438	0.263	0.2541
16	BES200 [25]	0.3417	0.2486	0.2443
17	Proposed ACSO	0.22321	0.23984	0.23199

7. Conclusion

In this paper, the ACSO has been productively implemented to solve ORPD problem. The main advantages of the ACSO to the ORPD problem are optimization of different type of objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints. The proposed algorithm has been tested on the IEEE 57-bus system. The active power loss has been minimized and the voltage profile indexes are within the limits.

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