



Science

ACTUAL POWER LOSS REDUCTION BY AUGMENTED PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract

This paper presents an advanced particle swarm optimization Algorithm for solving the reactive power problem in power system. Bacterial Foraging Optimization Algorithm (BFOA) has recently emerged as a very powerful technique for real parameter optimization. In order to overcome the delay in optimization and to further enhance the performance of BFO, this paper proposed a new hybrid algorithm combining the features of BFOA and Particle Swarm Optimization (PSO) called advanced bacterial foraging-oriented particle swarm optimization (ABFPSO) algorithm for solving reactive power problem. The simulation results demonstrate good performance of the ABFPSO in solving an optimal reactive power problem. In order to evaluate the proposed algorithm, it has been tested on IEEE 57 bus system and compared to other algorithms.

Keywords: Bacterial Foraging Optimization Algorithm; Particle Swarm Optimization; Optimal Reactive Power; Transmission Loss.

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1. Introduction

Main objective of optimal reactive power problem is to minimize the real power loss and bus voltage deviation. Different conventional techniques [1-8] have been already implemented to solve the optimal reactive power problem. Due to the difficulty in managing inequality constraints many algorithm fail to reach the global solution. Recently many types of Evolutionary algorithms have been used to solve optimal reactive power flow problem [9-10] & some algorithms good in exploration & some better in exploitation alone. Proposed algorithm equally balances the exploration & exploitation in the search of global solution in optimal reactive power problem. Natural selection tends to eliminate animals with poor foraging strategies and favour the propagation of genes of those animals that have successful foraging strategies since they are more likely to enjoy reproductive success. After many generations poor foraging strategies are either eliminated or shaped into good ones. Based on the researches on the foraging behavior of E-coli bacteria K.M. Passino proposed a new Evolutionary computation technique known as Bacterial

Foraging Optimization Algorithm (BFOA) [11], briefly explained in the following sections. However, during the process of chemo taxis, the BFOA depends on random search directions which may lead to delay in reaching global solution. In order to speed the convergence of Bacterial Foraging Optimization W. Karoni had proposed an improved BFOA namely BF-PSO [12]. The BF-PSO algorithm borrowed the ideas of velocity updating from particle swarm optimization (PSO), the search directions specified by the tumble of bacteria are oriented by the individual best location and global best locations concurrently. To reduce the time of optimization and to accelerate the convergence speed of group of bacteria near global optima for this BFO-PSO we propose a new hybrid algorithm "ABFPSO" in which the chemo tactic step had been made advanced. The performance of (ABFPSO) has been evaluated in standard IEEE 57 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

2. 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:

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (1)$$

Where g_k : is the conductance of branch between nodes i and j , Nbr : 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:

$$F = PL + \omega_v \times VD \quad (2)$$

Where ω_v : is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

Equality Constraint

The equality constraint is as follows:

$$P_G = P_D + P_L \quad (4)$$

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 are:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (6)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (7)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (8)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_c^{max}, i \in N_c \quad (9)$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

3. Bacterial Foraging Optimization Algorithm

Bacterial Foraging optimization is based on foraging behaviour of Escherichia coli (E. coli) bacteria present in the human intestine and been already implemented to real world problems [11,13]. The bacterial foraging process consists mainly of four sequential mechanisms namely chemo taxis, swarming and reproduction and elimination-dispersal.

- 1) **Chemo taxis:** - In the computational chemo taxis, the movement of i^{th} bacterium after one step can be represented as

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i)\varphi(j) \quad (10)$$

Here $\theta^i(j, k, l)$ denotes the location of i^{th} bacterium at j^{th} chemo tactic k^{th} reproductive and l^{th} elimination and dispersal step. $C(i)$ is the length of unit walk, which is constant in basic BFO and $\varphi(j)$ is the direction angle of the j^{th} step. When the bacterium is in run mode $\varphi(j)$ is same as $\varphi(j-1)$, otherwise $\varphi(j)$ is a random angle directed within a range of $[0, 2\pi]$. If the cost at $\theta^i(j+1, k, l)$ is better than the cost at $\theta^i(j, k, l)$, then the bacterium takes another step of size $C(i)$ in that direction otherwise it is allowed to tumble. This process is repeated until the number of steps taken is greater than the number of iterations in chemo tactic loop, N_c

- 2) **Swarming:** - The cell to cell signalling in E.coli swarm may be mathematically represented as

$$j_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^S j_{cc}(\theta, \theta^i(j, k, l)) = \sum_{i=1}^S \left[-d_{attractant} \exp\left(-\delta_{attractant} \sum_{m=1}^p (\theta_m - \theta_m^i)^2\right) \right] + \sum_{i=1}^S \left[h_{repellent} \exp\left(-\delta_{repellent} \sum_{m=1}^p (\theta_m - \theta_m^i)^2\right) \right] \quad (11)$$

Here $j_{cc}(\theta, P(j, k, l))$ represents objective function value to be added to actual objective function, S is the total number of bacteria, P is the number of parameters to be optimized and $\theta = [\theta_1, \theta_2, \dots, \theta_p]^T$ is a point in p-dimensional search domain. $d_{attractant}$ is the depth of attractant released by the cell and $\delta_{attractant}$ is the measure of width of the attractant signal. $h_{repellent} = d_{attractant}$ is the height of repellent effect magnitude, $\delta_{repellent}$ is a measure of width of repellent. These coefficients are to be taken judiciously.

- 3) **Reproduction:** - After the completion of all N_c chemo tactic steps a reproduction step takes place. Fitness value of the bacteria is stored in ascending order. The lower half of bacteria having a higher fitness die and remaining $S_r = S/2$ bacteria are allowed to split into two identical one. Thus the population after reproduction remains constant.
- 4) **Elimination and Dispersal:** - There is a probability that bacteria may be stuck around the initial or local optima positions, it is required to diversify the bacteria either gradually or suddenly so that the possibility of being trapped in to local minima is eliminated and global optima is obtained. The dispersion operation takes place after a certain number of reproduction processes. A bacterium is chosen, according to a present probability p_{ed} , to be dispersed and moved to another position within the environment. This may disturb optimization process but prevent the local minima trapping.

4. Hybrid of Bacterial Foraging Oriented with Particle Swarm Optimization

This combination aim is to make PSO capability to exchange social information and BF ability in finding new solution by elimination and dispersal, a unit length direction of tumble behaviour is randomly generated. Random direction may lead to delay in reaching the global solution. In "BF-PSO" algorithm the unit length random direction of tumble behaviour can be decided by the global best position and the best position of each bacterium. During the chemo taxis loop tumble direction is updated by:

$$\varphi(j + 1) = \omega * \varphi(j) + C_1 * rand * (pbest - pcurrent) + c_2 * rand * (gbest - pcurrent) \quad (12)$$

Where pbest is the best position of each bacterium and gbest is the global best bacterium. The brief pseudo-code of BF-PSO has been provided below. Algorithm to solve optimal dispatch problem described below

[Step 1] Initialize the parameters $p, S, N_c, N_s, N_{re}, N_{ed}, p_{ed}, C(i) (i = 1, 2, 3, \dots, S) \theta^i$

Where p –Dimension of the search space; S –Number of bacteria in the population; N_s –Swimming length after which tumbling of bacteria will be undertaken in chemotactic loop; N_c –The number of iterations to be undertaken in chemotactic loop, always $N_c > N_s$; N_{re} –Maximum no. of reproduction steps; N_{ed} –the maximum no. of Elimination and dispersal events to be imposed over bacteria; p_{ed} –Probability with which elimination and dispersal will continue; θ^i –Location of the

- i^{th} ($i = 1, 2, 3, \dots, S$) bacterium; $C(i)$ –Step size of the i^{th} bacterium taken in random direction, specified by tumble. Generate a random vector $\varphi(j)$ in the range $[-1, 1]$ C_1, C_2, ω : PSO parameters
2. Elimination and dispersal loop: $l = l+1$
 3. Reproduction loop: $k = k+1$
 4. Chemo taxis loop: $j = j+1$
 5. If $j < N_c$, go to [Step 4]. In this case, continue chemo taxis since the life of the bacteria is not over.
 6. Reproduction
 7. If $k < N_{re}$, go to the [Step 3]. Since in this case the specified reproduction steps are not reached, start the next generation of the chemo tactic loop.
 8. Elimination-dispersal: For $i = 1, 2, \dots, S$ with the probability p_{ed} , eliminate and disperse each bacterium, which results in keeping number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain. If $l < N_{ed}$ then go to [Step 2], otherwise end;

5. Advanced Bacterial Foraging Oriented Particle Swarm Optimization

To enhance the performance a simple advanced scheme for the step size for i^{th} bacterium given in following equation

$$C(i) = \frac{|j^i(\theta)|}{|j^i(\theta) + \Psi|} = \frac{1}{1 + \frac{\Psi}{j^i(\theta)}} \quad (13)$$

Where Ψ is positive constant, $j^i\theta = \text{cost function of the } i^{\text{th}} \text{ bacterium}$, $C(i) = \text{variable run (step) length of } i^{\text{th}} \text{ bacterium}$.

If $j^i\theta$ tends to zero then $C(i) \rightarrow 0$ and when $j^i\theta \rightarrow \text{large}$, $C(i) \rightarrow 0$. This implies that the bacterium which is in the vicinity of noxious substance associates with higher cost function. Hence it takes larger steps to migrate to a place with higher nutrient concentration. Use of Equation (10) in Equation (13) is expected to give improved convergence performance compared to fixed step size due to the above phenomenon.

[Step 1] Initialize the parameters $p, S, N_c, N_s, N_{re}, N_{ed}, p_{ed}, C(i) (i = 1, 2, 3, \dots, S) \theta^i$

Where p –Dimension of the search space; S –Number of bacteria in the population; N_s –Swimming length after which tumbling of bacteria will be undertaken in chemotactic loop; N_c –The number of iterations to be undertaken in chemotactic loop, always $N_c > N_s$; N_{re} –Maximum no. of reproduction steps; N_{ed} –the maximum no. of Elimination and dispersal events to be imposed over bacteria; p_{ed} –Probability with which elimination and dispersal will continue; θ^i –Location of the i^{th} ($i = 1, 2, 3, \dots, S$) bacterium; $C(i)$ –Step size of the i^{th} bacterium taken in random direction, specified by tumble. Generate a random vector $\varphi(j)$ in the range $[-1, 1]$ C_1, C_2, ω : PSO parameters

2. Elimination and dispersal loop: $l = l+1$

3. Reproduction loop: $k = k+1$

While updating location in Equation (10) (and also in swim) the advanced run length unit, $C(i)$ defined in Equation (13) is used instead of fixed run length unit.

4. Chemo taxis loop: $j = j+1$

5. If $j < N_c$, go to [Step 4]. In this case, continue chemo taxis since the life of the bacteria is not over.
6. Reproduction
7. If $k < N_{re}$, go to the [Step 3]. Since in this case the specified reproduction steps are not reached, start the next generation of the chemo tactic loop.
8. Elimination-dispersal: For $i = 1, 2, \dots, S$ with the probability p_{ed} , eliminate and disperse each bacterium, which results in keeping number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain. If $l < N_{ed}$ then go to [Step 2], otherwise end;

6. Simulation Results

Advanced bacterial foraging-oriented particle swarm optimization (ABFPSO) algorithm has been tested in standard IEEE-57 bus power system. The 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. The system variable limits are given in Table 1.

The preliminary conditions for the IEEE-57 bus power system are given as follows:

$$P_{load} = 12.572 \text{ p.u. } Q_{load} = 3.092 \text{ p.u.}$$

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

$$\sum P_G = 12.682 \text{ p.u. } \sum Q_G = 3.3278 \text{ p.u.}$$

$$P_{loss} = 0.25960 \text{ p.u. } Q_{loss} = -1.2062 \text{ p.u.}$$

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

Table 1: Variable Limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50
Voltage and Tap Setting Limits							
vgmin	Vgmax	vpqmin	Vpqmax	tkmin	tkmax		
0.9	1.0	0.91	1.05	0.9	1.0		
Shunt Capacitor Limits							
Bus no	18	25	53				
Qcmin	0	0	0				
Qcmax	10	5.2	6.1				

Table 2: Control variables obtained after optimization

Control Variables	ABFPSO
V1	1.1
V2	1.026
V3	1.018

V6	1.012
V8	1.002
V9	1.001
V12	1.012
Qc18	0.0542
Qc25	0.200
Qc53	0.0404
T4-18	1.002
T21-20	1.032
T24-25	0.854
T24-26	0.866
T7-29	1.045
T34-32	0.862
T11-41	1.010
T15-45	1.028
T14-46	0.900
T10-51	1.010
T13-49	1.020
T11-43	0.900
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [14]	0.25902	0.30854	0.27858
2	CGA [14]	0.25244	0.27507	0.26293
3	AGA [14]	0.24564	0.26671	0.25127
4	PSO-w [14]	0.24270	0.26152	0.24725
5	PSO-cf [14]	0.24280	0.26032	0.24698
6	CLPSO [14]	0.24515	0.24780	0.24673
7	SPSO-07 [14]	0.24430	0.25457	0.24752
8	L-DE [14]	0.27812	0.41909	0.33177
9	L-SACP-DE [14]	0.27915	0.36978	0.31032
10	L-SaDE [14]	0.24267	0.24391	0.24311
11	SOA [14]	0.24265	0.24280	0.24270
12	LM [15]	0.2484	0.2922	0.2641
13	MBEP1 [15]	0.2474	0.2848	0.2643
14	MBEP2 [15]	0.2482	0.283	0.2592
15	BES100 [15]	0.2438	0.263	0.2541
16	BES200 [15]	0.3417	0.2486	0.2443
17	Proposed ABFPSO	0.22002	0.23069	0.22298

7. Conclusion

In this paper a new hybrid algorithm combining the features of Bacterial Foraging Optimization Algorithm (BFOA) and Particle Swarm Optimization (PSO) called Advanced bacterial foraging-oriented particle swarm optimization (ABFPSO) algorithm successfully solved reactive power problem. The simulation results reveal good performance of the ABFPSO in solving an optimal reactive power problem. Proposed algorithm has been tested in standard IEEE 57 bus system and compared to other algorithms. Real power loss has been considerably reduced.

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