



Science

REAL POWER LOSS REDUCTION BY ENHANCED ACCLIMATIZED BACTERIAL EXPLORATION ALGORITHM

Dr.K.Lenin ^{*1}

^{*1} Professor, Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007, India



Abstract

This paper presents Enhanced Acclimatized Bacterial Exploration (EBE) algorithm to solve reactive power problem. Bacterial Search Optimization Algorithm has recently emerged as a very powerful technique based on the behaviour of E-coli bacteria. In order to speed up the convergence of Bacterial search Optimization Algorithm, this paper proposed a new hybridization between Bacterial Search Optimization Algorithm (BSO) and Particle Swarm Optimization (PSO). In order to evaluate the proposed Enhanced Acclimatized Bacterial Exploration (EBE) algorithm, it has been tested in standard IEEE 118 & practical 191 bus test systems and compared to other standard algorithms.

Keywords: Enhanced Acclimatized Bacterial Exploration Algorithm; Particle Swarm Optimization; Optimal Reactive Power; Transmission Loss.

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1. Introduction

Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1, 2], Newton method [3] and linear programming [4-7]. The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8,9]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [10]. This paper presents Enhanced Acclimatized Bacterial Exploration (EBE) algorithm to solve reactive power problem. Bacterial Search Optimization Algorithm has recently emerged as a very powerful technique based on the behaviour of E-coli bacteria. In order to speed up the convergence of Bacterial search Optimization Algorithm, this paper

proposed a new hybridization between Bacterial Search Optimization Algorithm (BSO) [11] and Particle Swarm Optimization (PSO) [12]. In order to evaluate the proposed Enhanced Acclimatized Bacterial Exploration (EBE) algorithm, it has been tested in standard IEEE 118 & practical 191 bus test systems and compared to other standard algorithms.

2. Problem Formulation

The OPF problem is considered as a general minimization problem with constraints, and can be 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

3.1. 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:

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

Or

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

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.

3.2. 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:

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

3.3. 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.

3.4. 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, N_T is the total number of Transformers; N_C is the total number of shunt reactive compensators.

4. Bacterial Search Optimization Algorithm

Bacterial Search Optimization Algorithm (BSO) is based on foraging behaviour of Escherichia coli (E.coli) bacteria present in the human intestine and been already implemented to real world problems [13]. In this foraging theory, the objective of the animal is to search for and obtain nutrients in a fashion that energy intake per unit time (E/T) is minimized [11]. A group of bacteria move in search of food and away from noxious elements known as Foraging. BSO algorithm draws its inspiration from this foraging behaviour. Bacteria have a tendency to gather to the nutrient-rich areas by activity called Chemo taxis. Its movement and behaviour is characterized by the spinning flagella which acts as a Biological motor and helps bacteria to swim. An e.coli bacterium has 8-10 flagella placed randomly on its body with a speed of 100-200 rps. An E.coli bacteria alternate through running and sinking. Running speed is 10-20m/s and they cannot swim straight. The flagella can rotate either clockwise or counter clockwise. When all the flagella rotate counter clockwise, they form a compact, helically propelling the cell along a trajectory, which is called "run". When the flagella rotate in clockwise direction they enable the bacterium to move in different directions and cause bacteria to "tumble". The bacterial foraging process consists mainly of four sequential mechanisms namely chemo taxis, swarming and reproduction and elimination-dispersal.

4.1. Chemo Taxis

An E.coli bacterium can move in two different ways: it can run (swim for a period of time) or tumble and alternates between these movements throughout its travel in search of food. In BSO, a unit walk with random direction represents a "tumble" and a unit walk with the same direction in the last step indicates "run". In the computational chemo taxis, the movement of i^{th} bacterium after one step can be represented as

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i)\varphi(j) \quad (17)$$

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

4.2. Swarming

A bacterium in times of stresses releases attractants to signal the bacteria to swarm together. Each bacterium also releases repellent to signal the others to be at a minimum distance from it. Thus all of them will have a cell to cell attraction via attractant and cell to cell repulsion via repellent. The cell to cell signalling in E.coli swarm may be mathematically represented as

$$j_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^S j_{cc}(\theta, \theta^i(j, k, l)) = \sum_{i=1}^S \left[-d_{attractant} \exp\left(-\delta_{attractant} \sum_{m=1}^p (\theta_m - \theta_m^i)^2\right) \right] + \sum_{i=1}^S \left[h_{repellent} \exp\left(-\delta_{repellent} \sum_{m=1}^p (\theta_m - \theta_m^i)^2\right) \right] \quad (18)$$

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.

4.3. 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.

4.4. 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.

5. Enhanced Acclimatized Bacterial Exploration (EBE) Algorithm

This paper presents Enhanced Acclimatized Bacterial Exploration (EBE) algorithm to solve reactive power. In order to speed up the convergence of Bacterial search Optimization Algorithm (BSO), this paper proposed a new hybridization between Bacterial Search Optimization Algorithm (BSO) and Particle Swarm Optimization (PSO). The aim is to make PSO ability to exchange social information and BSO 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 EBE 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:

$$\varphi(j + 1) = \omega * \varphi(j) + C_1 * rand * (pbest - pcurrent) + c_2 * rand * (gbest - pcurrent) \quad (19)$$

Where pbest is the best position of each bacterium and gbest is the global best bacterium.

Chemo taxis is a foraging strategy that implements a type of local optimization where the bacteria try to climb up the nutrient concentration, avoid noxious substance and search for ways out of neutral media. A chemo tactic step size varying as the function of the current fitness value is expected to provide better convergence behaviour as compared to a fixed step size. A simple adaption scheme for the step size for i^{th} bacterium given in following equation

$$C(i) = \frac{|j^i(\theta)|}{|j^i(\theta) + \Psi|} = \frac{1}{1 + \frac{\Psi}{j^i(\theta)}} \quad (20)$$

Where Ψ is positive constant, $j^i\theta$ = cost function of the i^{th} bacterium, $C(i)$ = variable run (step) length of i^{th} 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 Eqn (20) in Eqn (17) 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

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

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

Step 4 Chemo taxis loop: $j = j + 1$: While updating location in Eqn (17) the adaptive run length unit, $C(i)$ defined in Eqn (20) is used instead of fixed run length unit.

Step 5 If $j < N_c$, go to [Step 4]. In this case, continue chemo taxis since the life of the bacteria is not over.

Step 6 Reproduction

Step7 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.

Step8 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

At first Enhanced Acclimatized Bacterial Exploration (EBE) algorithm has been tested in standard IEEE 118-bus test system [14].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 1, with the change in step of 0.01.

Table 1: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 2 and the results clearly show the better performance of proposed Enhanced Acclimatized Bacterial Exploration (EBE) algorithm.

Table 2: Comparison results

Active power loss (p.u)	BBO [15]	ILSBBO/strategy1 [15]	ILSBBO/strategy1 [15]	Proposed EBE
Min	128.77	126.98	124.78	115.94
Max	132.64	137.34	132.39	119.36
Average	130.21	130.37	129.22	116.28

Then the Enhanced Acclimatized Bacterial Exploration (EBE) algorithm has been tested in practical 191 test system and the following results have been obtained. In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 3 shows the optimal control values of practical 191 test system obtained by EBE method. And table 4 shows the results about the value of the real power loss by obtained by Enhanced Acclimatized Bacterial Exploration (EBE) algorithm.

Table 3: Optimal Control values of Practical 191 utility (Indian) system by EBE method

VG1	1.10	VG 11	0.90
VG 2	0.72	VG 12	1.00
VG 3	1.01	VG 13	1.00
VG 4	1.01	VG 14	0.90
VG 5	1.10	VG 15	1.00
VG 6	1.10	VG 16	1.00
VG 7	1.10	VG 17	0.90
VG 8	1.01	VG 18	1.00
VG 9	1.10	VG 19	1.10
VG 10	1.01	VG 20	1.10

T1	1.00	T21	0.90	T41	0.90
T2	1.00	T22	0.90	T42	0.90
T3	1.00	T23	0.90	T43	0.91
T4	1.10	T24	0.90	T44	0.91
T5	1.00	T25	0.90	T45	0.91
T6	1.00	T26	1.00	T46	0.90
T7	1.00	T27	0.90	T47	0.91
T8	1.01	T28	0.90	T48	1.00
T9	1.00	T29	1.01	T49	0.90
T10	1.00	T30	0.90	T50	0.90
T11	0.90	T31	0.90	T51	0.90
T12	1.00	T32	0.90	T52	0.90
T13	1.01	T33	1.01	T53	1.00
T14	1.01	T34	0.90	T54	0.90
T15	1.01	T35	0.90	T55	0.90
T19	1.02	T39	0.90		
T20	1.01	T40	0.90		

Table 4: Optimum real power loss values obtained for practical 191 utility (Indian) system by EBE method

Real power Loss (MW)	EBE
Min	143.192
Max	147.184
Average	144.126

7. Conclusion

Proposed Enhanced Acclimatized Bacterial Exploration (EBE) algorithm has been successfully solved reactive power problem. Enhanced Acclimatized Bacterial Exploration (EBE) algorithm is applied to obtain the optimal control variables so as to minimize the real power loss the system. The proposed Enhanced Acclimatized Bacterial Exploration (EBE) algorithm has been tested in standard IEEE 118 & practical 191 bus test systems. And the results were compared with other standard algorithms. Simulation study make known about the most excellent

performance of the proposed algorithm in dropping the real power loss and voltage profiles are well within the limits.

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*Corresponding author.

E-mail address: gklenin@ gmail.com