Indonesian Journal of Electrical Engineering and Computer Science
Vol. 13, No. 1, January 2019, pp. 361~367
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v13.i1.pp361-367

A modified bacterial foraging algorithm based optimal reactive power dispatch

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Article Info

Article history:

Received Apr 22, 2018
Revised Nov 20, 2018
Accepted Nov 27, 2018

Keywords:

Chaotic dynamics
Chemotaxis enhanced bacterial foraging algorithm
Differential mutation
OLTC
Optimal reactive power dispatch
Shunt capacitors
Voltage deviations

ABSTRACT

This article describes an approach for optimal reactive power dispatch problem using a Modified Bacterial Foraging Algorithm. Modified bacterial foraging algorithm introduces a differential evolution operator in chemotaxis to overcome tumble failure in tumble step and accelerates the convergence speed of the original operator. In the new algorithm chaotic dynamics are used to generate initial population to have uniform distribution. The proposed new algorithm is applied to Optimal reactive power dispatch problem with two objective functions; minimization of real power loss and voltage stability L-index. The objective functions are minimized by optimally choosing the control variables such as generator excitations, tap positions of on-load tap changing transformers and switched var compensators. The proposed approach has been evaluated on an IEEE 30 bus standard test system. The performance of the proposed algorithm is compared with other evolutionary computation algorithms in the literature and the effectiveness of the proposed algorithm is demonstrated

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1. INTRODUCTION

The primary objective of Energy control centre is to maintain the power system in a secure and stable state by continuously monitoring the power flows in the lines and voltage magnitudes at the buses. Voltage variations are due to the imbalance of reactive power generated and consumed by the node. These voltage variations can be corrected by co-ordinated control of voltage/reactive power control devices such as generator excitations, on-load tap changing transformers and switchable shunt VAR compensating devices. The complexity of power system operation is increasing day by day because of growing demand and without matching generation and transmission facilities resulting transmission as well as generation operated with smaller safety margins. Under these conditions, it is great challenge to optimize the power system and ensure the security.

Optimal Reactive Power Dispatch (ORPD) problem is a non linear optimization problem with multiple objectives and constraints. This problem has been solved by a number of conventional optimization techniques such as Linear programming (LP), Non linear programming (NLP), Quadratic programming etc. are reported in the literature [1-6]. However, these conventional algorithms have some limitations such as differentiation of objective function is required and curse of dimentionality. These limitations can be overcome if evolutionary computation techniques are adapted because of their approach of random search and begin with a population of solutions and also no differential information is required. There are various evolutionary computation techniques such as Particle Swarm optimization algorithm, Gravitational search algorithm, Firefly algorithm, Differential evolution algorithm, ant colony algorithm, BAT algorithm etc. are reported in the literature [7-11] for ORPD problem.

Bacterial Foraging Algorithm (BFA) is one of the population based evolutionary computation algorithms which is proposed by Passino. This algorithm is inspired by foraging strategy of E.coli bacteria. Though original BFA algorithm is used by many experts in different fields, it has some drawbacks of slow convergence speed and not taken into account on the diversity of population which can easily lead to the premature convergence when dimension increases. Yuan –tao Zhang et al. [12-13] proposed adaptive chemotaxis step setting and chaotic perturbation in each chemo tactic to improve the original BFA. Fuqing Zhao et al.[14-15] proposed a chmotaxis enhanced BFA by introducing differential mutation operator and chaotic operator in chemotaxis step. Na Dong et al.[16] proposed chaotic PSO algorithm by introducing chaos dynamics to generate initial population and chaotic perturbation in to swarm updation.

The present paper proposes a Modified Bacterial Foraging algorithm (MBFA) which utilizes the differential mutation operator to enhance the tumble step in chemotaxis to overcome tumble failure and chaos dynamics to generate uniformly distributed initial population. The proposed algorithm is applied to solve the optimal reactive power dispatch with two objectives minimization of real power loss and voltage stability L-index. The performance of the proposed algorithm is tested on IEEE 30 bus standard test system and results are compared with other evolutionary techniques available in the literature on this problem. The superiority of proposed algorithm is demonstrated.

2. PROBLEM FORMULATION

The proposed algorithm is applied to two objective functions: minimization of real power loss and voltage stability L-index.

2.1. Transmission loss objective (Ploss):

The real power loss of the system can be calculated as follows

$$P_{loss} = \sum_{k=1}^{N_{line}} g_k (V_i^2 - V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j))\ MW \tag{1}$$

Where P_{loss} is the total real power loss, N_{line} is total number of transmission lines. $V_i and\ V_j$ are the voltage magnitudes at the two ends of the K^{th} line. $\theta_i\ and\ \theta_j$ are the voltage angles at the two ends of the K^{th} line. Voltage magnitudes and angles can be caluculated from the load flow solution. g_k is the conductance of the K^{th} line.

2.2. Voltage stability index objective (Vstability):

Voltage stability L-index is considered as measure to find voltage stability.

$$L_{max} = \max(L_j) \tag{2}$$

L-index can be computed as

$$L_j = \left| 1 - \sum_{i=1}^{g} F_{ji} \frac{v_i}{v_j} \right| \tag{3}$$

Where j indicates all the load buses. v_i and v_j are voltage magnitudes at i^{th} and j^{th} buses and they can be taken from load flow. Fji can be obtained from the Ybus matrix as follows

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \tag{4}$$

Rearranging the above equation we get

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{5}$$

Where I_G, I_L and V_G, V_L indicate currents and voltages of the generator and load buses. $F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}]$ are the required values. The L-index values for a given load condition are computed for all the load busses.The range of L-index value is 0-1. As it is closer to zero, it indicates better stability and the improved system security. As it approaches 1, it indicates closer to voltage collapse. Stability index L_j must not be violated the maximum limit for any of the load buses. An L-index value away from 1 and close to zero indicates an improved system security. So $(1-L_j)$ indicates the margin of stability.

2.3. +Constraints

The two objective functions are minimized by optimally choosing the three control variables; Transformer tap settings, Generator excitations settings and Switchable VAR compensating settings.

The constraints on these control variables are given as.

$$\begin{aligned} &t_{ij}^{min} \leq t_{ij} \leq t_{ij}^{max},\ i \in T \\ &V_i^{min} \leq V_i \leq V_i^{max},\ i \in N_g \\ &Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max},\ i \in N_{qc} \end{aligned} \tag{6}$$

Where t_{ij} represents the tap setting of transformer connected between i-j buses, N_g is the set of generator buses, V_i represents the generator bus voltage of i^{th} bus, Q_{ci} represents the reactive power compensation capacity of i^{th} bus and N_{qc} is the set of load buses with reactive power support. There are two dependent variables, reactive power output of the generators and voltage of all load buses, which will be effected during optimization. So the constraints on these dependent variables need to be considered while performing optimization. They are given as:

$$\begin{aligned} &Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max},\ i \in N_g \\ &V_i^{min} \leq V_i \leq V_i^{max},\ i \in N_L \end{aligned} \tag{7}$$

Q_{gi} represents the reactive power generated by the i^{th} generator. V_i is the voltage magnitude at load bus i and N_L is number of load buses.

The constraints on control variables are adjusted to their limits, if they exceed, before determining the objective functions. The constraints on dependent variables are dealt by using penalty factor method. By considering this objective functions change as follows.

$$P_{loss} = \sum_{k=1}^{N_{line}} g_k(V_i^2 - V_j^2 - 2V_iV_j\cos(\theta_i - \theta_j)) + \beta_1 \sum_{i=1}^{N_L}\left(\frac{(V_i - V_i^{lim})}{(V_i^{max} - V_i^{min})}\right)^2 + \beta_2 \sum_{i=1}^{N_G}\left(\frac{(Q_{gi} - Q_{gi}^{lim})}{(Q_{gi}^{max} - Q_{gi}^{min})}\right)^2 \tag{8}$$

$$\mathrm{L}_{\max} = \max(L_j) + \beta_1 \sum_{i=1}^{N_L}\left(\frac{(V_i - V_i^{lim})}{(V_i^{max} - V_i^{min})}\right)^2 + \beta_2 \sum_{i=1}^{N_G}\left(\frac{(Q_{gi} - Q_{gi}^{lim})}{(Q_{gi}^{max} - Q_{gi}^{min})}\right)^2 \tag{9}$$

β_1, β_2 *are penalty factors.* V_i^{lim}, Q_{gi}^{lim} can be expressed as

$$V_i^{lim} = \begin{cases} V_i^{max}, V_i > V_i^{max} \\ V_i^{min}, V_i < V_i^{min} \\ V_i, others \end{cases} \quad Q_{gi}^{lim} = \begin{cases} Q_{gi}^{max}, Q_{gi} > Q_{gi}^{max} \\ Q_{gi}^{min}, Q_{gi} < Q_{gi}^{\min} \\ Q_{gi}, others \end{cases} \tag{10}$$

3. MODIFIED BACTERIAL FORAGING ALGORITHM

3.1. Chemo taxis insufficient of Original BFA

In the original algorithm, search begins with population of bacteria, where each bacteria is a potential solution of the optimization problem. The population is converged towards optimal solution by following the foraging strategy of bacteria. This process consists of chemotaxis, reproduction and elimination and dispersion. Chemotaxis step simulates the movement of E.coli bacteria through tumbling and swimming via flagella. Chemotactic movement is continued until a bacteria goes in the direction of positive nutrient gradient i.e. increasing the fitness. It is achieved through tumbling and swimming. The chemotaxis movement of the bacterium can be represented as

$$\theta^i(j,k,l) = \theta^i(j,k,l) + c(i)\ \phi(j), \phi(j) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{11}$$

Here $\theta^i(j,k,l)$ represents the position vector of i^{th} bacterium for the j^{th} chemotaxis step, k^{th} reproduction step and l^{th} elimination dispersal step. c(i) is step size taken in the random direction specified by the tumble. $\phi(j)$ is direction angle taken by tumble at j^{th} step. If the fitness at $\theta^i(j+1,k,l)$ is better than the fitness at $\theta^i(j,k,l)$ then the bacterium takes another few step sizes c(i) in that direction specified by swim length. If the fitness at $\theta^i(j+1,k,l)$ is not better than the fitness at $\theta^i(j,k,l)$ then bacterium does not go for swim, it finds another direction through tumble. But this will affect the algorithm because many a times it may not find better position. It slows down the algorithm search speed and may settle at local optimum. In this way original chemotactic step of BFA cannot effectively stabilise the searching process. In order to improve the chemotaxis, different measures are to be taken to stimulate the static individual baterium to do extra movement.

3.2. Differential Evolution operator

The following differential evolution operator is selected by considering the parameter setting of BFA.

$$v_d^i = \theta_d^i(j,k,l) + F(\theta_d^{gbest}(j,k,l) - \theta_d^{R2}(j,k,l) + \theta_d^{R1}(j,k,l) - \theta_d^{R3}(j,k,l)) \tag{12}$$

where d refers to the dimension of solution. $\theta_d^i(j,k,l)$ represents the position vector of i^{th} bacterium for the j^{th} chemotaxis step, k^{th} reproduction step and l^{th} elimination dispersal step. v_d^i represents i^{th} bacterium during differential mutation . θ_d^{gbest} is the global best of the solutions, $\theta_d^{R1}, \theta_d^{R2}$, θ_d^{R3} are three individual bacteria that are randomly chosen from the whole group. F is the differential factor whose range is [0.2 – 0.9]. By using the information of best individual in the current population, the speed of the over all search is accelerated. Besides, by taking full advantage of the information of other individuals in the population, degradation of individual dimention is prevented and the probability of the individual trapped in to the local optimal is reduced.

3.3. Incorporating Chaotic Dynamics into initial population

Since it gives the uniform distribution function in the interval [0, 1], the tent map is chosen in this paper. The chaotic dynamics of the tent map is used for generating initial population. The tent map is defined by,

$$z_j^{i+1} = \mu\left(1 - 2\left|z_j^i - 0.5\right|\right)\ j = 1,2, - - - D. \tag{13}$$

where z_j denotes the jth chaos variable and i denotes the chaos iteration number. Set i = 0 and generate D chaos variables by (@). Then i=1,2, - - - N, generate N population of initial bacteria. Then the chaos variable z_j^i, i=1,2, - - , N is mapped in to the the search range of descision variable by the following equation.

$$x_{ij} = x_{min,j} + z_j^i\left(x_{max,j} - x_{min,j}\right)\ j = 1,2, - - - D \tag{14}$$

Where x_{ij} is i^{th} bacteria of j^{th} descision variable. $x_{min,j}$ is minimum limit on j^{th} descision variable and $x_{max,j}$ is maximum limit on j^{th} descision variable.

3.4. Algorithmic Steps for ORPD with modified BFA

To apply BFA algorithm, the following steps have to be followed.

Step 1: Read the system data. Set the parameters of the BFA.
Step 2: Choose initial population of bacteria with chaotic dynamics of tent map (13-14).
Step 3: Elimination dispersion loop, l=l+1, k=0.
Step 4: Reproduction loop: k=k+1, j=0.
Step 5: Chemotaxis loop: j=j+1, Check the bacteria for the constraints.
Step 6: Get the fitness value of objective functions (8-9) from NR load flow solution. Perform tumble by adding random vector to the bacteria. Calculate the fitness, if it is better than previous, perform swim for swim size otherwise use differential mutation operator to update positon of bacteria. If the maximum number of chemotactic steps (N_c) is reached go to next step, otherwise go to step 5 and continue.
Step 7: Sort the bacteria according to their fitness. Remove the worst half of the population and replace them with the best half. If maximum number of reproduction steps (N_{re}) is reached go to nextstep otherwise go to step 4 and continue.

Step 8: Eliminate the bacteria with new one with the probability of P_{ed} i.e if a random number is greater than P_{ed}. If maximum number of elimination and dispersion steps is reached go to next step otherwise go to step 3 and continue.
Step 9: Print the results.

4. RESULTS AND DISCUSSION

The proposed modified Bacterial Foraging algorithm is applied to the ORPD problem with two objective functions, minimization of real power loss (Ploss) and voltage stability L-index (Vstability). The evolution is carried out on standard IEEE 30 bus test system. System data and initial settings are adapted from [17]. It consists of 30 buses, 41 branches, 6 generators, 4 tap setting transformers and 9 switchable VAR compensating sources. Buses 1,2,5,8,11 and 13 are generator buses. Reactive power sources are installed at buses 10,12, 15, 17, 20, 21, 23, 24 and 29. Branches (6-9), (6-10), (4-12) and (28-27) are equipped with OLTC transformers. The voltages of generator buses and load buses have been constrained within limits between 0.95p.u and 1.1p.u. Operating range of all OLTCs is range from 0.9 to 1.1. The range of capacitor banks is considered between 0 MVAr to 5 MVAr.

Table 1 shows the simulation results for Ploss objective. The Proposed MBFA algorithm reduced the power loss from base value 5.812 MW to 4.5978 MW, which indicates 20% reduction from the base value. There is also 0.006 MW reduction of power loss in comparison with ALO algorithm which is lowest among other evolutionary computation algorithms presented in the table for comparison. There is also 0.11 MW reduction of power loss in comparison with the basic BF algorithm. The proposed algorithm is also giving a 6% reduction of L_{max} value for P_{loss} objective in comparison with BA which is lowest among the algorithms from literature.

Table 1. Comparision of simulation results for Ploss objective

	initial	BA [18]	GWO [18]	ABC [18]	ALO [18]	HDESA [19]	GAFGP [20]	BFA	MBFA
VG1	1.05	1.1	1.1	1.1	1.1	1.0744	1.055	1.1	1.098
VG2	1.04	1.094	1.0938	1.0971	1.0953	1.0724	1.042	1.0956	1.0946
VG5	1.01	1.074	1.0737	1.0866	1.0767	1.0486	1.035	1.068	1.0798
VG8	1.01	1.076	1.0797	1.08	1.0788	1.498	1.036	1.0761	1.0817
VG11	1.05	1.1	1.1	1.085	1.1	1.0692	1.085	1.1	1.0965
VG13	1.05	1.1	1.0944	1.1	1.1	1.0038	1.064	1.0953	1.1
T6-9	1.078	0.95	0.98	1.07	1.01	1.0375	0.9536	1.0195	1.0459
T6-10	1.069	1.03	0.97	0.95	0.99	0.9938	0.9067	0.9848	0.9052
T4-12	1.032	0.99	1.02	1.02	1.02	0.975	0.999	1.0283	0.9759
T28-27	1.068	0.97	0.99	1.01	1	1.0438	0.9662	0.9493	0.9688
QC10	0	5	2	5	4	0.011	0.03871	4.0169	3.5902
QC12	0	0	5	0	2	0.033	0.04151	1.9792	4.5386
QC15	0	5	4	2	4	0.0465	0.04812	0	3.5325
QC17	0	5	4	5	3	0.035	0.03735	3.0222	4.5453
QC20	0	0	4	4	2	0.0335	0.04617	2.9253	4.8974
QC21	0	0	0	5	4	0.018	0.04828	2.0375	1.2546
QC23	0	0	5	4	3	0.007	0.03781	1.0387	4.4724
QC24	0	5	3	5	5	0.017	0.04512	4.0035	4.9146
QC29	0	0	3	4	5	0.0155	0.0269	2.0401	1.3196
Ploss	**4.812**	**4.628**	**4.611**	**4.611**	**4.59**	**5.129**	**5.169**	**4.694**	**4.584**
Lmax	0.1716	0.1247	0.1303	0.1326	0.1307	NR	NR	0.1189	0.1176

All the simulations are done in MATLAB R2009b software on a personal computer with configuration i3 processor, CPU 1.9GHz and 4GB RAM. 30 independent runs were executed and best, worst and mean values of optimal solutions are presented. The obtained results of proposed Modified BFA are compared with basic BFA and other standardard evolutionary algorithms in the literature such as Bat algorithm (BA), Grey wolf optimization (GWO), Artificial Bee colony (ABC), Ant Loin Optimization (ALO), Hybrid differential Evolution and Simulated Annealing (HDESA), Genetic Algorithm based Fuzzy Goal Programming (GAFGP) and Gravitational Search Optimization (GSO) algorithm.

Table 2 the simulation results for Vstability objective. The Proposed MBFA algorithm reduced the power loss from base value 0.1716 to 0.1139, which indicates 33% reduction from the base value. There is also 2% of reduction of L_{max} value from ALO algorithm which is lowest among other evolutionary algorithms presented in the table for comparison. The proposed algorithm also offered 3% reduction from the basic BFA. Figure 1 shows the convergence of BFA and MBFA algorithms for 100 iterations for P_{loss} and $V_{stability}$ objectives.

Table 2. Comparision of simulation results for Vstability objective

	initial	BA [18]	GWO [18]	ABC [18]	ALO [18]	GSO [21]	BFA	MBFA
VG1	1.05	1.097	1.0965	1.0829	1.0992	1.1	1.0591	1.0997
VG2	1.04	1.093	1.0807	1.073	1.0948	1.1	1.0569	1.0989
VG5	1.01	1.049	1.0693	1.0759	1.0975	1.1	1.0409	1.0783
VG8	1.01	1.071	1.0624	1.0744	1.0997	1.1	1.0893	1.0484
VG11	1.05	1.06	1.0977	1.1	1.0979	1.1	1.0637	1.0965
VG13	1.05	1.097	1.0927	1.0804	1.1	1.1	0.9674	1.0913
T6-9	1.078	1.09	0.96	1.03	1.04	0.9	0.9794	0.9416
T6-10	1.069	0.9	1.01	0.92	0.95	0.9	0.9654	1.058
T4-12	1.032	1.1	0.97	0.92	0.98	0.9	0.9059	0.9884
T28-27	1.068	0.93	0.94	0.97	0.97	1.019538	0.9325	0.9453
QC10	0	3	2	5	5	5	3.0287	5
QC12	0	4	1	5	3	5	3.994	5
QC15	0	3	1	5	3	5	3.0276	5
QC17	0	5	2	4	4	5	1.8953	5
QC20	0	5	2	5	3	5	1.9395	4.9763
QC21	0	0	1	3	2	5	3.9801	4.9456
QC23	0	0	4	4	1	5	4.0131	5
QC24	0	0	4	4	2	5	4.0236	4.9768
QC29	0	3	4	5	4	5	4.0333	4.943
Ploss	4.812	5.0748	4.8269	4.9688	4.8693	6.660258	6.652	4.954
Lmax	**0.1716**	**0.1191**	**0.118**	**0.1161**	**0.1161**	**0.11607**	**0.1174**	**0.1137**

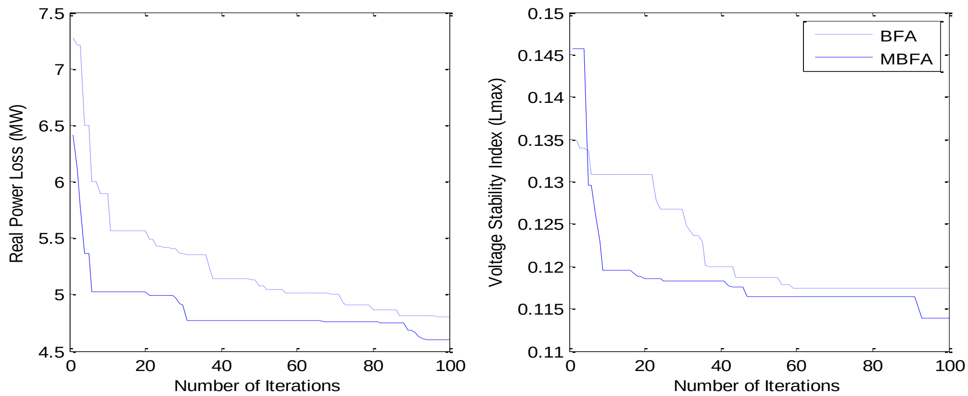

Figure 1. Convergence of BFA and MBFA for P_{loss} and $V_{stability}$ objectives

Table 3 shows summary of the performance of both the algorithms. It clearly shows the out performance of the proposed algorithm for both the objectives. Generally evolutionary computation algorithms are random in nature they vary from one run to another run. But the standard deviation value shows that the proposed algorithm is more consistant which is very much desirable in practical applications.

Table 3. Summary of BFA and MBFA performance

	BFA	MBFA		BFA	MBFA
Ploss best	4.694	4.584	Lmax best	0.1174	0.1137
Ploss worst	5.138	4.706	Lmax worst	0.1258	0.1173
Ploss mean	4.906	4.638	Lmax mean	0.1212	0.1148
Ploss STD	0.1169	0.042	Lmax STD	0.0022	0.0011

5. CONCLUSIONS

Reactive power optimization with a Modified Bacterial Foraging algorithm for two objectives; minimization of real power loss and voltage stability L- index is proposed. The proposed algorithm is tested on IEEE 30 bus test system. Simulation results obtained by the proposed MBFA are compared with original BFA and also with other popular techinuques which are reported in the recent state of art literatures and it is demonstrated that there is significant improvement in both objectives in comparison with original BFA and also giving better results in comparison with other algorithms. The results also demonstrate that addition of differential mutation and chaos dynamics improved the original BFA algoritm to a considerable degree and with consistency. So the proposed algorithm is suitable for Energy Control Center.

REFERENCES

[1] J.Qiu and S.M.Shahidehpour, "*A new approach for minimizing power losses and improving voltage profile,*" *IEEE Trans. On Power Systems*, vol.2, no.2, May 1987, pp.287-295

[2] Bansilal, D. Thukaram, K. Parthasarathy, "*Optimal reactive power dispatch algorithm for voltage stability improvement*," *Int. Journal of Electrical Power and Energy Systems* 18 (7) (1996) 461-468.

[3] D. Thukaram, K. Parthasarathy, H. P. Khincha, Narendranath Udupa and A. Bansilal, "*Voltage stability improvement: case studies of Indian power networks*," *Electric Power Systems Research,* vol.44, 1998, pp.35-44.

[4] J.Z.Zhu and X.F.Xiong, "*Optimal reactive power control using modified interior point method*," *Electric Power Systems Research,* vol.66, 2003, pp.187-192.

[5] Thukaram Dhadbanjan, G. Yesuratnam, "*Comparison of Optimum Reactive Power Schedule with Different Objectives Using LP Technique*", International Journal of Emerging Electric Power Systems, 2006, Volume 7, Issue 3, Article 4

[6] Abraham Lomi, D Thukaram, "*Optimum Reactive power dispatch for Alleviation of Voltage Deviations*" TELKOMNIKA (Telecommunication Computing Electronics and Control), vol 10, No.2, June 2012, pp.257-264.

[7] Mohamad Khairuzzaman Mohamad Zamani, Ismail Musirin, Mohamad Sabri Omar, Saiful Izwan Suliman, Nor Azura Md. Ghani, Nur Azwan Mohamed Kamari "*Gravitational Search Algorithm Based Technique for Voltage Stability Improvement" Indonesian Journal of Electrical Engineering and Computer Science (IJEECS),* Vol 9, No 1, January 2018, pp.123-130.

[8] Xiao G, Liu H, Zhou Y, Guo Y Research on Chaotic Firefly algorithm and the application in optimal reactive power dispatch' TELKOMNIKA (Telecommunication Computing Electronics and Control), 2017; 15(1): 93-100

[9] Slimani L, Bouktir T, Optimal Power Flow Solution of Algerian Electrical Network Using Differential Evolution Alogorithm', *TELKOMNIKA (Telecommunication Computing Electronics and Control),* 2012; 10(2): 199-210.

[10] R Katuri, G Yesuratnam, A Jayalaxmi, " BAT algorithm and Ant Colony Optimization based Optimal Reactive Power Dispatch to Improve Voltage Stability*" European Journal of Engineering Research and Science* 2 (6), 27-35, 2017

[11] Laxmi Srivastava, Himmat Singh, "Hybrid multi-swarm particle swarm optimisation based multi-objective reactive power dispatch", IET Gener. Transm. Distrib, 2015, Vol. 9, Iss. 8, pp. 727–739

[12] Yuan tao ZHANG, Chao HUANG 'An improved Bacterial foraging based approach to Data clustering" Artificial Intelligence Science and Technology, 2016.

[13] Yuan tao ZHANG, Chao HUANG 'A Novel Adaptive Choatic Bacterial foraging Optimization Algorithm" DEStech transactions on Computer Science & Engineering, November 2016.

[14] Faqing Zhao, Xin Jiang, Chuk Zhang and Junbiao Wang " A Choatic Local Search Based Bacterial Foraging Algorithm and its Application to a permutation flow Shop Scheduling Problem" International Journal Computer Integrated Manufacturing, 2015

[15] Faqing Zhao, Xin Jiang, Chuk Zhang and Junbiao Wang "A Chmotaxis Enhanced Bacterial Foraging Algorithm and its Application in Job Shop Scheduling Problem" International Journal Computer Integrated Manufacturing, 2015

[16] Na Dong, Xing Fang, Ai-guoWu, "A Novel Chaotic Particle Swarm Optimization Algorithm for Parking Space Guidance", Mathematical Problems in Engineering, Hindawi Publishing Corporation, Volume 2016, Article ID 5126808, 14 pages

[17] Lee, K.Y., Park, Y.M., and Oritz, J.L., "Optimal Real and Reactive Power Dispatch", Electric Power Research, 1984; 7; 201-219

[18] Souhil Mouassa, Tarek Bouktir , Ahmed. Salhi, "Ant lion optimizer for solving optimal reactive power dispatch problem in power systems", Engineering Science and Technology, an International Journal 20 (2017) 885–895

[19] Farida Laouafi, Ahcene Boukadoum, Salah Leulmi "*A Hybrid Formulation between Differential Evolution and Simulated Annealing Algorithms for Optimal Reactive Power Dispatch*", *TELKOMNIKA (Telecommunication Computing Electronics and Control),* Vol 16, No 2: April 2018, pp. 513-524.

[20] Biswas P, Pal BB, "A Trilevel Programming Approach to Solve Reactive Power Dispatch Problem Using Genetic Algorithm Based Fuzzy Goal Programming", Proceedings of the 48th annual convention of CSI, 2014; 1:205-217.

[21] S.Duman, Y Sonmez, U Guvenc , N Yorukeren "Optimal Reactive Power using a gravitational search algorithm" IET Gener Transm, Distrib, 2012, vol 6,iss 6, pp 563-576