

Colliding bodies optimization algorithm for optimal reactive power dispatch

Anbarasan P* and Jayabarathi T**

Abstract: This paper presents a novel, meta-heuristic optimization algorithm for the problem of optimal reactive power dispatch in the areas of power system operation and control. The optimal reactive power dispatch problem is huge, and is constrained by a wide range of non-linear and non-convex optimization problems. This optimal reactive power dispatch problem was formulated by generator output voltages (continuous variable), tap changing transformers and a number of switchable VAR devices (discrete variables). This algorithm was established on one-dimensional collisions between bodies, with each operator solution being treated as an object or body with mass. After the collision of two moving bodies with named masses and velocities, these bodies were detached with new velocities. This collision caused the operators to act towards superior positions in the search space. The optimization of the colliding bodies utilized simple formulations to find minimum or maximum of functions and did not depend on any internal parameter. The proposed colliding bodies optimization algorithm was tested on IEEE-6 bus and IEEE-14 bus systems. The improved result values were compared with Evolutionary programming, DE algorithm, dynamic particle swarm optimization, self-adaptive real coded genetic algorithm and modified Gaussian bare bones teaching-learning based optimization.

Keywords: *Evolutionary algorithm, optimal reactive power dispatch, Loss minimization, and colliding bodies algorithm.*

1.0 INTRODUCTION

The problem of reactive power control is challenging and has been a big driving duty for power system operators over the past two and half decades. If any parameters like power expansion in electricity need, increase of the grid capacity, season, weather conditions, the expansion of power market and contingency vary in power system area due to load variations, they can change the voltage magnitudes in various levels. When such a situation occurs, the system operators have the duty to (i) maintain acceptable level of voltage magnitude in power system network for both current and contingency conditions (ii) reduce the congestion of real power flows in transmission line and (iii) reduce

the real power loss in transmission lines. Also, they should ensure that sufficient power supply is dispatched to the customer side with quality, accuracy, security, stability and economically. These targets are achieved by reallocating the optimal level of reactive power supply from reactive compensation devices such as automatic voltage regulators, tap changing transformers and switchable VAR devices in suitable location of power system area by satisfying the equality and inequality constraints.

In the past, many conventional techniques like gradient method, linear programming method, Newton's method and interior point methods etc., were used to obtain the optimal solution. As a result of mathematical formations, moving

*Assistant professor (selection grade) School of Electrical Engineering Vellore Institute of Technology, vellore, India panbarasan@vit.ac.in

**Professor, School of Electrical Engineering, Vellore Institute of Technology, Vellore, India tjayabarathi@vit.ac.in

closer constraints, suffering convergence, [1-6] meeting the chances of global optimum, these methods have failed to solve the nonlinear and non-convex type of optimization problem. Also, their computational procedure is too long and expensive in large scale power system.

Hence, the conventional method optimization techniques are unable to offer satisfied solutions. In the past two and half decades, new meta heuristics algorithms have been developed for obtaining an optimal solution. These algorithm techniques are powerful for handling the different subjective constraints, offering global optimal solution in single simulation run in multi objective optimization problem. Some of the meta heuristics optimization technique algorithms have recently been used for solving ORPD problems. Dynamic particle swarm optimization [13], genetic algorithm [14], DE algorithm [16], self-adaptive real coded genetic algorithm [10] and teaching learning based [21] etc.

This paper is organized as follows: The objective functions and ORPD problems are represented in section II. The CBO algorithm is denoted in section III. The CBO algorithm implementation part is discussed in section IV. The test system results and discussion are presented in section V. Finally, the conclusion is given in section VI.

2.0 FORMULATION OF ORPD PROBLEM

The objective function of the ORPD is to minimize the real power loss (P_L) in the transmission lines of a power system network. The ORPD problem in general operating condition can be composed by

$$P_L = \sum_{k=1}^{Nl} g_k [(t_k V_i)^2 + V_j^2 - 2t_k V_i V_j \cos\theta_{ij}] \quad \dots(1)$$

Where P_L is real power loss; 'k' is transmission line enclosed bus 'i' and 'j'; n_l is the number of transmission lines; g_k is conductance of branch 'k' enclosed bus 'i' and 'j'; t_k is the tap ratio of transformer 'k'; V_i is the voltage magnitude at bus 'i'; V_j is the voltage magnitude at bus 'j';

θ_{ij} is voltage angle difference between buses 'i' and 'j'

A. Constraints

The minimization of the objective function equation (1) is organized to the number of equality and inequality constraints. The constraints are described as follows:

B. Equality constraints

The equilibrium constraints on state variables are given by

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{Nb} V_j (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) = 0 \quad \dots(2)$$

$$Q_{gi} - Q_{di} + Q_{ci} - V_i \sum_{j=1}^{Nb} V_j (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) = 0 \quad \dots(3)$$

where, n_b is number of buses, n_{pv} is number of generator buses, and n_{pq} is number of load buses, g_{ij} , b_{ij} are the mutual conductance and susceptance between bus 'i' and 'j' respectively; P_{gi} , Q_{gi} are real and reactive power generation at bus 'i'; P_{di} , Q_{di} are real and reactive power demand at bus 'i'; Q_{ci} the reactive power compensation source at bus 'i';

C. Inequality constraints

The inequality constraints on security limits are given by

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad \dots(4)$$

$$V_i^{min} \leq V_i \leq V_i^{max} \quad \text{for } i = 1 \dots n_{pq} \dots(5)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad \text{for } i = 1 \dots n_g \dots(6)$$

$$S_1 \leq S_1^{max} \quad \text{for } 1 = 1 \dots n_l \quad \dots(7)$$

The inequality constraints on control variable limits are given by

$$V_{gi}^{\min} \leq V_{gi} \leq V_{gi}^{\max} \text{ for } i = 1 \dots n_{pv} \quad \dots(8)$$

$$t_k^{\min} \leq t_k \leq t_k^{\max} \text{ for } i = 1 \dots n_t \quad \dots(9)$$

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max} n_c \text{ for } i = 1 \dots n_c \quad \dots(10)$$

Where, n_g is number of generators; n_t is number of transformers; n_c number of compensator device; S_i is the apparent power flow in transmission line ‘1’;

Hence, the equation (1) is replaced by the following Formation

$$F = R_L + (P_{gi,slack} - P_{gi,slack}^{lim})^2 + \lambda V_i \sum_{i=1}^{NI} (V_i - V_i^{lim})^2 + \lambda Q_{Gi} \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}^{lim})^2 \quad \dots(11)$$

Where λV_i λQ_{Gi} are the penalty terms in equation (11). They are defined as follows:

$$\begin{cases} V_i^{lim} = V_i^{\min} & \text{if } V_i < V_i^{\min} \\ V_i^{\max} & \text{if } V_i > V_i^{\max} \end{cases}$$

$$\begin{cases} Q_{Gi}^{lim} = Q_{Gi}^{\min} & \text{if } Q_{Gi} < Q_{Gi}^{\min} \\ Q_{Gi}^{\max} & \text{if } Q_{Gi} > Q_{Gi}^{\max} \end{cases}$$

The objective function of the power system is computed using load flow calculation with the equality and inequality constraints specified above.

3.0 DESCRIPTION OF CBO ALGORITHM

Colliding bodies optimization (CBO) is a new meta-heuristic search algorithm developed by Kaveh and Mahdavi . In this technique, one object collides with another object, and they move towards a minimum energy level. The CBO is simple in concept and does not depend

on any internal parameter. Each colliding body (CB), X_i , has a specified mass defined as:

$$m_k = \frac{1}{[fit(k)]} / \left[\frac{1}{\sum_{i=1}^n \frac{1}{[fit(i)]}} \right]$$

Where $fit(i)$ represents the objective function value of the i^{th} CB and ‘n’ is the number of colliding bodies. In order to select pairs of objects for collision, CBs are sorted according to their mass in a decreasing order, and they are divided into two equal groups: (i) stationary group, (ii) moving group. Moving objects collide with stationary objects to improve their positions and push stationary objects towards better positions.

4.0 THE PROPOSED APPROACH TO SOLVE THE ORPD BY CBO ALGORITHM

Step:1. Select the system for which the loss is to be minimized by ORPD. The system should specify, the number of control variables within the specified limit in network. The bus data and line data of the standard IEEE system

Step 2: The ORPD variables in the network which represent each colliding body position are chosen, and they consist of the generator output voltage, transformer tap settings and reactive power of VAR devices that are randomly generated within their limits. Thus, the i^{th} position of CB.

$$X_i = [V_{g2}, V_{g3}, \dots, V_{gn}, \dots, t_1, t_2, \dots, n_t, Q_{c1}, Q_{c2}, \dots, Q_{cn}]$$

The complete search space for CBO algorithm having population P is expressed as follows

$$X = [X_1, \dots, X_2, \dots, X_p]^T$$

Step 3. The objective function of each CB as follows

$$F = R_L + (P_{gi,slack} - P_{gi,slack}^{lim})^2 + \lambda V_i \sum_{i=1}^{NI} (V_i - V_i^{lim})^2 + \lambda Q_{Gi} \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}^{lim})^2 \quad \dots(12)$$

Where P_L is the objective function to be minimized. λV_i , and λQ_{Gi} , are penalty terms of the corresponding constraints.

Step 4: The body mass of each CB is calculated as

$$m_k = \frac{1}{fit(k)} / \left[\frac{1}{\sum_{i=1}^n \frac{1}{fit(i)}} \right]$$

Where $fit(k)$ is the fitness value of k th CB

Step 5: Now the CBs are sort in ascending order according to their mass values. The sorted values are divided equally into two groups. The velocity of stationary and moving objects before the collision is defined as

$$v_i = 0 \quad i=1,2,\dots,n/2$$

Where X_i is the i^{th} CB position vector.

Step 6. The velocity of stationary and moving CBs after the collision (v'_i) are evaluated by

$$v'_i = \frac{(m_{i+\frac{n}{2}} + \epsilon m_{i-\frac{n}{2}})v_{i+\frac{n}{2}}}{m_i + m_{i+\frac{n}{2}}} \quad i = 1, 2 \dots \frac{n}{2}$$

$$v'_i = \frac{(m_i - \epsilon m_{i-\frac{n}{2}})v_i}{m_i + m_{i-\frac{n}{2}}} \quad i = \frac{n}{2} + 1, \frac{n}{2} + 2 \dots n$$

Where ϵ is the co-efficient of restitution and it is defined as follows

$$\epsilon = 1 - \frac{iter}{iter_{max}}$$

Where $iter$ and $iter_{max}$ are the current iteration number and the total number of iteration for Optimization process, respectively.

Sep 7: New position of each CB are updated by

$$x_i^{new} = x_i + rand^{\circ} v_i \quad i=1,2,\dots,n/2$$

$$x_i^{new} = x_{i-in/2} + rand^{\circ} v_i \quad i=n/2+1, n/2+2, \dots, n$$

where x_i (v'_i)

and the velocity after the Collision of the i^{th} CB, respectively.

Step 8: check, If any control variables are violating the constraint value.

Step 9: If the maximum number of iterations are reached, then stop the procedural steps. Otherwise go to step 3.

5.0 NUMERICAL RESULTS

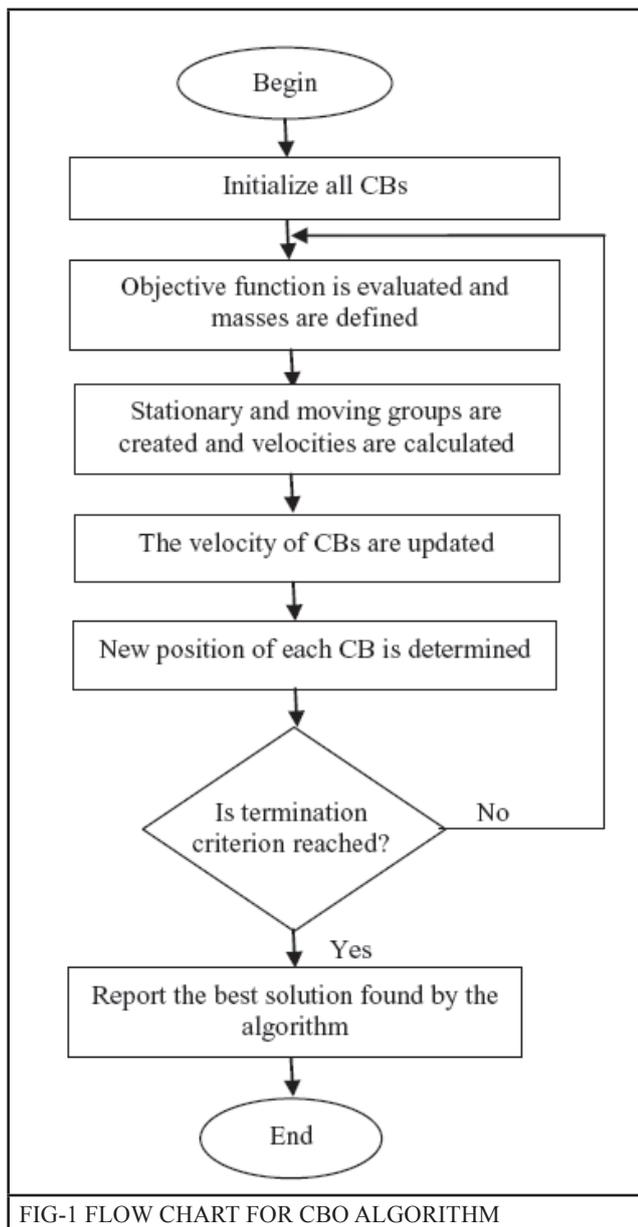
In this section, the CBO algorithm approach is tested for standard IEEE-6 and 14 bus systems whose loads and initial active power generations are similar as in the base case [9, 12, & 13]. The procedural steps are followed based on flow chart shown in figure -1. The following control variable parameters are considered in the ORPD problems.

- (i) The generator output voltage – continuous variable
- (ii) Tap changing transformer –Discrete variable
- (iii) VAR compensators – Discrete variable

The ORPD problem is solved with 100 MVA base for all the test cases. The Newton-Raphson load flow method is used for monitoring the equality and inequality constraint violation. The results obtained by simulation of the CBO algorithm done in MATLAB 2015 on a Intel(R), core(TM) i3-3110 cpu @2.40 GHz, 4.00 GB RAM processor.

A. Case -1 IEEE-6 bus system

In IEEE-6 bus system, bus 1 is slack bus, bus 2 is generator bus, 3,4,5 and 6 are load buses and 7 lines in which 2 are tap changing transformers in transmission lines (4-3 and 6-5). The switchable VAR compensators are connected on buses 4 and 6. In total, 6 ORPD control variables are taken from 6-bus system. The system data, operating constraints and base transmission line loss 11.61 MW are taken from [13].Table 1 gives the control variable limits for 6 bus system.



Variables	Lower limit p.u.	Upper limit p.u.	Discrete value
Generator	$V_1=1.0$	$V_1=1.1$	-
Bus voltage	$V_2=1.1$	$V_2=1.15$	
Transformer Tap	$T_{43} = 0.91$ $T_{65} = 0.91$	$T_{43} = 1.1$ $T_{65} = 1.1$	0.91+16*1.25
VAR installation (MVAR)	$Q_4 = 0.0$	$Q_4 = 5.0$	10*0.5
	$Q_6 = 0.0$	$Q_6 = 5.5$	10*0.5

In this case, the system parameters caused a variation in the taping point of the transformers with 16 steps of 0.0125 p.u. each and two shunt compensation capacitor banks with 10 steps of 0.5 p.u and 0.55 p.u each on bus number 4 and 6 respectively.

The CBO algorithm does not require any internal parameters such as other meta heuristic algorithms for solving ORPD problem and it attempts to move the population size for better solutions.

Control variables (p.u)	Optimization technique Method			
	Base case	GA	DPSO	CBOA
Variable				
V_{G1}	1.05	1.1	1.1	1.1
V_{G2}	1.1	1.15	1.15	1.15
Q_4	0	5	5	5
Q_6	0	5	5.5	5.5
T_{4-3}	1.1	1.0475	0.9475	0.9450
T_{6-5}	1.025	1.085	0.9350	0.9283
$P_{loss}(MW)$	11.6123	8.7700	8.7036	8.3721
% Loss reduced		24.46%	25.03%	27.90%

By assuming a suitable population size, number of varying ORPD variables and maximum number of iterations, the MAT lab programme was run. After running every independent trial, the optimum variables were obtained in 200th iteration and the population size was 40. This result and control variables are shown in Table-2. The loss values for 6-bus system of CBO algorithm were compared with DPSO & GA. It was observed that the loss minimization improved by 4.06 % from DPSO and 3.44% from GA

The convergence characteristics of CBO algorithm of 6 bus are shown in figure-2. From the convergence characteristics, we observed that the CBO algorithm performed better from 15 to 20 iterations and offered good solutions by comparing it with the paper [13]

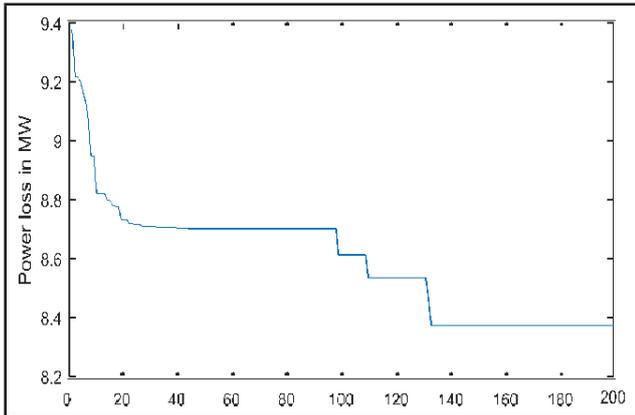


FIG. -2 CONVERGENCE CHARACTERISTICS OF IEEE-6 BUS

B. case -2 IEEE 14 bus system.

TABLE 3 CONTROL VARIABLE SETTINGS FOR 14 BUS SYSTEMS				
Test cases	Variables	Min p.u.	Max. p.u.	Step
14 bus	V _G	0.90	1.10	0.01
	V _{PQ}	0.90	1.10	
	T	0.90	1.10	
	B _{SH9}	0.0	0.18	
	B _{SH14}	0.0	0.06	

TABLE 4 POWER LOSS & BEST CONTROL VARIABLE FOR IEEE - 14				
Control variables (p.u)		Optimization technique method		
Variable	PSO	SARGA (2009)	MGBTLO (2015)	CBOA
VG2	1.0463	1.096	1.0791	1.0863
VG3	1.0165	1.036	1.0484	1.0568
VG6	1.1000	1.099	1.0553	1.0500
VG8	1.1000	1.078	1.0326	1.0901
T4-7	0.9400	0.95	1.01	1.0220
T4-9	0.9300	0.95	1.01	0.9538
T5-6	0.9700	0.96	1.03	1.0718
SC9	0.18	0.18	0.3	0.18
SC14	0.0600	0.06	0.07	0.06
Ploss(MW)	13.327	13.2164	12.3105	12.0013
%Loss reduced	1.21%	2.03%	8.74%	11.04%

In IEEE-14 bus system, bus 1 is slack bus, 2, 3, 6 and 8 are generator buses, 9 load buses and 20 lines in which 3 lines (4-7, 4-9 and 5-6) are tap changing transformers. The switchable VAR compensators are connected on buses 9 and 14. Totally, 10

ORPD variables are taken from 14 bus system. The system data, operating constraints and base transmission line loss 13.49 MW were taken from [10]. Table 3 gives the control variable limits for 14 bus system.

In this case, the system parameters varied the tap change of the transformers with 20 steps of 0.01 p.u of each and two shunt compensation capacitor banks with 3 steps of 0.06 p.u. of each on bus number 9 and 1 step of 0.06 p.u. on bus number 14.

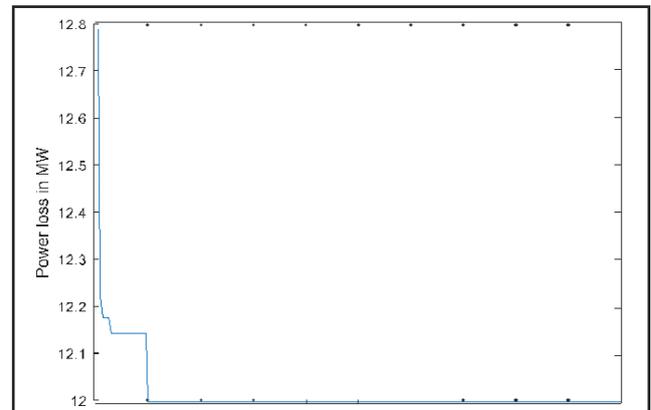


FIG. -3 CONVERGENCE CHARACTERISTICS OF IEEE-14 BUS

In 14 bus system also the population size, number of varying ORPD variables and maximum number of iterations were assumed suitably and the MAT lab programme was run.. This result and control variables are shown in Table-4. The loss values for 14-bus system of CBO algorithm compared with PSO, SARGA & MGBTL. It is observed that the loss minimization is improved by 1.21% from PSO, 2.03% from SARGA, 8.74% from MGBT and 11.04% from CBO algorithm.

The convergence characteristic of 14-bus system is shown in figure-(3). The CBO algorithm converged very quickly from 10-15 iterations, and it was faster than SARGA algorithm.[10]

6.0 CONCLUSION

This paper reports a matured meta-heuristics CBO algorithm that was carried out to deal with ORPD problem thoroughly. This optimization

technique was performed by varying the reactive power constraint variables such as generator output voltage, transformer tapping point and VAR compensator in 6 bus and 14 bus data. The active power loss obtained by this new meta heuristic CBO algorithm was minimum and it showed superior results compared to other techniques (the same data) PSO, EP, DPSO, MGBTLO. This algorithm revealed the number of iterations, convergence characteristics, data processing optimization strategy, and committed efficient method for handling constraints. The proposed CBO algorithm is energetically recommended for future researchers for solving complex engineering optimization problems.

NOMENCLATURE

CBO - Colliding bodies optimization algorithm
 ORPD - optimal reactive power dispatch
 EP - evolutionary programme
 DPSO- dynamic particle swarm optimization
 SARGA - self-adaptive real coded genetic algorithm
 DEA - Differential evolutionary algorithm
 MGBTLBO - modified Gaussian bare bone teaching learning based optimization algorithm
 P_L - Power loss
 k - Transmission line between bus 'i' and 'j'
 g_k - conductance of branch 'k' between bus 'i' and 'j'
 t_k - Tap ratio of transformer 'k' V_i –voltage magnitude at bus 'i' V_j –voltage magnitude at bus 'j'
 θ_{ij} - is voltage angle difference between buses 'i' and 'j'
 n_b - is number of buses
 n_{pv} - number of generator buses n_{pq} - is number of load buses
 g_{ij}, b_{ij} - are the mutual conductance and susceptance between bus 'i' and 'j' respectively

P_{gi}, Q_{gi} -are real and reactive power generation at bus 'i'
 P_{di}, Q_{di} - are real and reactive power demand at bus 'i'
 Q_{ci} - is the reactive power compensation source at bus 'i';
 n_g - is number of generators
 n_t - is number of transformers;
 n_c - number of compensator device
 S_l - is the apparent power flow in transmission line 'l';

REFERENCES

- [1] H.W.Dommel, W.F.Tinney. Optimal power flow solutions. IEEE, Trans. On power Apparatus and Systems, VOL. PAS-87, October 1968,pp.1866-1876.
- [2] Lee K, Park Y, Ortiz J. A. United approach to optimal real and reactive power dispatch. IEEE Trans Power Appar. Syst. 1985; 104(5):1147-53.
- [3] D.I. Sun, B. Ashley, B. Brewar, A. Hughes, W.F. Tinny, Optimal power flow by Newton approach, IEEE Trans. Power Appar. syst. 103 (1984) 2864–2880.
- [4] V.H. Quintana, M. Santos-Nieto, Reactive-power dispatch by successive quadratic programming, IEEE Trans. Energy Conv. 4 (1989) 425–435.
- [5] Deeb NI, Shahidehpour SM. An efficient technique for reactive power dispatch using a revised linear programming approach. Electric Power System Research 1988;15:121–34.
- [6] S. Granville, Optimal reactive power dispatch through interior point methods, IEEE Trans. Power Syst. 9 (1994) 136–146.
- [7] Wood, A.J., Wallenberg, B.F.: 'Power generation operation and control' (John Wiley & Sons, Inc., New York, 1996, 2nd edn.)
- [8] Saadat H. Power system analysis. 2nd ed. New York: McGraw-Hill; 2004.

- [9] Hirotaka Yoshida, Kenichi Kawata, Yoshikazu Fukuyama, *Member; IEEE*, Shinichi Takayama, and Yosuke Nakanishi, *Member; IEEE* A “Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment” *IEEE Transactions On Power Systems*, Vol. 15, No. 4, November 2000
- [10] P.Subbaraj, P.N.Rajnarayanan. “Optimal reactive power dispatch using self-adaptive real coded genetic algorithm” *Electric Power System Research* Vol. 79 pp. 374-381, (2009)
- [11] Power system case archive. Available at <http://www.ee.washington.edu/research/pstca/>
- [12] Altaf Q, H. Badar*, B.S.Umre, A.S.Junghare. “Reactive power control using dynamic Particle swarm Optimization for real power loss minimization” *Electrical Power and Energy Systems* Vol. 41 pp. 133-136. (2012)
- [13] Haibo Zhang, Lizi Zhang, Fanling Meng “Reactive power Optimization on Genetic Algorithm”
- [14] M.A. Abido, Optimal power flow using particle swarm optimization, *J. Electr. Power Energy Syst.* 24 (2002) 563–571.
- [15] M.Varadarajan, K.S.Swarup “Differential evolutionary algorithm for optimal reactive power dispatch” *Electrical power and Energy Systems* 30 (2008) 435-441.
- [16] C.F.Ionescu, M.Eremia, Senior member IEEE, C.Bulac, Member IEEE “Reactive power optimization using Evolutionary Techniques; Differential Evolution and Particle Swarm.”
- [17] El Ela A, Abido MA, Spea SR. Differential evolution algorithm for optimal reactive power dispatch. *Electric Power System Research* 2011; 81:458–64.
- [18] Ayana K, Kılıc U. Artificial bee colony algorithm solution for optimal reactive power flow. *Appl Soft Comput* 2012; 12:1477–82.
- [19] T. Malakara, S.K. Goswami, 1 Active and reactive dispatch with minimum control movements *Electrical Power and Energy Systems* 44 (2013) 78–87
- [20] Mojtaba Ghasemia, n, Mahdi Taghizadeha, ahand Ghavidel a, Jamshid Aghaeia, Abbas Abbasian b “Solving optimal reactive power dispatch problem using a novel teaching–learning-based optimization algorithm” *Engineering Applications of Artificial Intelligence* 39 100–108 (2015)
- [21] M.Y.Cheng, D.Prayogo, Symbiotic organism search: a new meta-heuristics optimization algorithm, *computer Structure.* 139, 98-112 (2014)
- [22] C.H. Liang, C.Y. Chung, K.P. Wong, X.Z. Duan, C.T. Tse, Study of differential evolution for optimal reactive power flow, *IET Gen. Transm. Distrib.* 1 (2007) 253–260.