Hybrid Big Bang - Big Crunch Algorithm for Optimal Reactive Power Dispatch by Loss and Voltage Deviation Minimization

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Abstract.

Power system voltage security is improved by optimizing reactive power dispatch (ORPD). ORPD problem is a multi-constrained, multi-objective problem involving both continuous and discrete control variables. An efficient optimization technique is needed for handling such a challenging objective function. Generator bus voltages, transformer tap positions and shunt Var compensator settings are the design variables in optimizing reactive power. ORPD problem is attacked by intelligent algorithms in recent years. In this work, the newly proposed, Big Bang–Big Crunch algorithm is suggested for reactive power optimization problem due to its simplicity and better convergence behavior. This algorithm is efficient in local search but sometimes global searching behavior is not sufficient. The global searching ability of particle swarm optimization (PSO) is adopted to enhance the BB-BC algorithm. The resultant is a hybrid BB-BC algorithm, the HBB-BC algorithm. The efficiency of the HBB-BC algorithm is tested on the standard IEEE-30 bus system for ORPD. The results are compared with that of basic BB-BC algorithm. The improved results encourage implementing this hybrid algorithm for different power system optimizations.

Keywords:

Optimal Reactive Power Dispatch, Big Bang–Big Crunch Algorithm, Particle Swarm Optimization Algorithm, Optimal Reactive Power Dispatch, Loss Minimization, Voltage Deviation Minimization.

I. INTRODUCTION

Modern power system networks are facing increased load demand and there are risks of stability problems. Non-optimized reactive power flow in a power system increases the transmission loss and threatens the security of the system. In general, reactive power dispatch is optimized by real power loss minimization. Reactive power optimization is done for reasons of power system security [1]-[3]. When a power system is under heavily loaded conditions, the demand for reactive power is more than that for real power. Increased demand for reactive power may affect the system security. Sufficient reactive power generation should be made available for avoiding system instability.

To ensure adequate reactive power generation reactive power planning for the future was suggested by many researchers [4]. But it requires installation of new Var sources and the capital cost. This problem can also be dealt with by optimizing the reactive power generation from the existing var sources. Minimization of reactive power generation is equivalent to maximization of reactive reserves and it may be useful when additional var is required [5]. Var flow in a power system is optimized by controlling generator bus voltages, transformer tap positions and existing Var sources like SVCs [6]. Among these parameters transformer tap positions and SVCs settings are discrete variables and generator bus voltages are continuous variables. Hence, ORPD is a mixed inter optimization problem and it is not so easy to find a global optimal solution.

Conventional optimization algorithms such as linear programming [6], nonlinear programming [7] and quadratic programming [8] are used for ORPD problem. In [9], Newton method is exploited for solving ORPD problem. Interior point method is used in [10] for optimizing reactive power. However, these methods are efficient and have certain drawbacks like their inability to handle non-continuous and non-differentiable objective functions, trapping into local optima. Evolutionary algorithms are introduced to overcome those drawbacks. Some of the evolutionary algorithms include simple genetic algorithms [11], evolutionary programming [12], particle swarm optimization [13]-[14] and differential evolution [2].

In this work, the nature inspired BB-BC algorithm is proposed for reactive power optimization. This algorithm is simple, easy for implementation and has less number of parameters. The objectives considered are real power loss and voltage deviation.

This remaining content of paper is organized as follows: Section 2 describes the problem formulation which is related to the objective function. Section 3 deals with the hybrid BB-BC algorithm and its implementation for ORPD. Numerical results are discussed in section 4. Finally, conclusions are drawn in section 5.

II. PROBLEM FORMULATION

The objective of this work is to optimize the reactive power flow in a power system by minimizing the real power loss and sum of load bus voltage deviation. Therefore, an augmented objective function is formed with the two objective components with suitable weights.

Objective function

Three different objective functions are considered in this work. The design parameter values corresponding to the minimum value of the objective functions are identified. The objective functions can be expressed as:

$$f_1 = min\{P_{loss}\} \quad (1)$$

$$f_2 = min\{VD\} \quad (2)$$

$$f_3 = min\{wP_{L+}(1-w)VD\} \quad (3)$$

Where 'w' is the weighing factor for real power loss andvoltage deviation and is set to 0.7.

Real power loss minimization (PL)

The total real power of the system can be calculated as follows.

$$P_{loss} = \sum_{K=1}^{N_L} G_k\left[V_i^2 + V_j^2 - 2|V_i||V_j|cos\delta_i - \delta_j\right] \quad (4)$$

Where, NL is the total number of lines in the system; G_k is the conductance of the line 'k', Vi and Vj are the magnitudes of the sending end and receiving end voltages of the line;δ_i and δ_j are angles of the end voltages.

Load bus voltage deviation minimization (VD)

Bus voltage magnitude should be maintained within the allowable range to ensure quality supply of electrical power. Voltage profile is improved by minimizing the deviation of the load bus voltage from the reference value (it is taken as 1.0 p.u. in this work).

$$V_D = \sum_{k=1}^{N_{PQ}} \left|V_i - V_{ref}\right| \quad (5)$$

Constraints

The minimization problem is subject to the followingequality and inequality constraints

Equality constraints

Load Flow Constraints:

The equality constraints represent the load flow equations, which are given below for ith bus:

$$P_{Gi} - P_{Di} = \sum_{j=1}^{NB} V_i V_j Y_{ij} cos(\delta_{ij} + \gamma_j - \gamma_i) \quad (6)$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{NB} V_i V_j Y_{ij} sin(\delta_{ij} + \gamma_i - \gamma_j) \quad (7)$$

Where,P_{Gi} ,Q_{Gi} are the active and reactive power of ith generator, P_{Di} , Q_{Di} the active and reactive power of ith load bus.

Inequality constraints

Generator constraints:

Generator voltage and reactive power of ith bus lies between their upper and lower limits as given below:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} \; i = 1,2,\dots.N_G \quad (8)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \; i = 1,2,\dots.N_G \quad (9)$$

Where, V_{Gi}^{min} , V_{Gi}^{max} are the minimum and maximum voltage of ith generating unit and Q_{Gi}^{min} , Q_{Gi}^{max} are the minimum and maximum reactive power of ithgenerating unit.

Load bus constraints:

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max} \; i = 1,2,\dots.N_L \quad (10)$$

Where, V_{Li}^{min} , V_{Li}^{max} are the minimum and maximum value voltage of load bus 'i'.

Transmission line constraints:

$$S_{Li} \le S_{Li}^{max} \; i = 1,2,\dots,N_{TL} \quad (11)$$

Where, S_{Li} is the apparent power flow of ith branch and S_{Li}^{max} is the maximum apparent power flow limit of ith branch.

Transformer taps constraints:

Transformer tap settings are bounded between upper and lower limit as given below:

$$T_{Pi}^{max} \le T_{Pi} \le T_{Pi}^{max} \; i = 1,2,\dots,N_T \quad (12)$$

Where, T_i^{max} , T_i^{max} are the minimum and the minimum and maximum tap setting limits of i[th] transformer.

Shunt compensator constraints:

Shunt compensation are restricted by their limits as follows:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, \quad i = 1,2\ldots, Q_{C\ NC} \quad (13)$$

Where, Q_{Ci}^{min} , Q_{Ci}^{max} are the minimum and maximum VAR injection limits of i[th] shunt capacitor.

III. BIG BANG – BIG CRUNCH ALGORITHM

III.1 The Basic BB-BC Algorithm

A new nature inspired optimization technique which has low computational time and high convergence speed what is called BB-BC is introduced recently [15]-[16]. The algorithm consists of two simple phases,

1. Big Bang phase
2. Big Crunch phase.

In Big Bang phase, candidate solutions are randomly distributed over the search space. The main feature of Big Bang phase is that the energy dissipation produces disorder and randomness. In Big Crunch phase, the randomly distributed solutions are drawn into an order and shrinks to a single solution called centre of mass. The Big Bang-Big Crunch optimization method generates random solutions in the Big Bang phase and shrinks these points to the global best point in the Big Crunch phase after a number sequential Big Bangs and Big Crunches.

The Big Bang phase is followed by the Big Crunch phase. The Big Crunch is a convergence operator that has many inputs but only one output, which is named as the centre of mass, since the only output has been derived by calculating the centre of mass. The centre of mass is the best solution among the solutions. In this work, the centre of mass is calculated according to the following expression.

$$X_C = \frac{\sum_{i=1}^{NP} \frac{1}{f(X_i)} X_i}{\sum_{i=1}^{NP} \frac{1}{f(X_i)}} \quad (14)$$

Where, Xi is a point within an D-dimensional search space, f(Xi) is a fitness function value of this point, NP is the population size in Big Bang phase. The convergence operator in the Big Crunch phase is different from 'exaggerated' selection since the output term may contain additional information (new candidate or member having different parameters than others) than the participating ones, hence differing from the population members. This one step convergence is superior compared to selecting two members and finding their centre of gravity. This method takes the population members as a whole in the Big Crunch phase that acts as a squeezing or contraction operator; and it, therefore, eliminates the necessity for two-by-two combination calculations.

After the Big Crunch phase, the algorithm must create new agents to be used as the Big Bang of the next iteration step. Latter iterations use the knowledge gained from the previous ones for generation of agents; hence, the convergence of such an algorithm is good. In this work, the new candidates are generated around the centre of mass and knowledge of centre of mass of previous iteration is used for better convergence. The parameters to be supplied to normal random point generator are the centre of mass of the previous step and the standard deviation. The deviation term can be fixed, but decreasing its value along with the elapsed iterations produces better results.

$$X_i^{t+1} = X_c^{t+1} + \frac{r\alpha\left(X_i^{max} - X_i^{min}\right)}{t+1} \quad (15)$$

Where, 'r' is a normal random number, α is a parameter limiting the size of the search space, X_{max} and X_{min} are the upper and lower limits, and t is the iteration step. Since normally distributed numbers can be exceeding ±1, it is necessary to limit the population to the prescribed search space boundaries. This narrowing down restricts the candidate solutions into the search space boundaries.

III.2 The Hybrid HBB-BC Algorithm [17]-[18]

The BB-BC algorithm is good in exploitation of the search space but not so good or some sluggishness is there in exploration. If all of the candidates in the initial Big Bang are collected in a small area of search space, the BB–BC method may not find the optimum solution and with a high probability, it may be trapped to a small region in the solution space.

Large number of agents may be taken to ensure that the search space is exploited well, but it results in large number offunctional evaluations and computational burden. The exploration efficiency of the algorithm can be improved by hybridizing it with PSO algorithm. PSO is motivated from the social behaviour of bird flocking and fish schooling which has a population of individuals, called particles, that adjust their movements depending on both their own experience and the population's experience [19]. At each iteration, a particle moves towards a direction computed from the best visited position (particle best) and the best visited position of all particles in its neighbourhood (global best). The hybrid BB–BC approach similarly not only uses the centre of mass but also utilizes the best position of each candidate (X_i^{best}) and the best global position ($X_{g\ best}^t$) to generate a new solution, as:

$$X_i^{t+1} = \left\{ \begin{matrix} \propto_2 X_c^t + (1-\propto_2)(\propto_3 X_{g\ best}^t + (1-\propto_3) X_i^{best}) \\ + \dfrac{rand \propto_1 (X_i^{max} - X_i^{min})}{t+1} \end{matrix} \right\} \quad (16)$$

Where, X_i^{t+1} is the new agent for the next iteration; $\propto_1, \propto_2, \propto_3$ are random numbers in the range [0,1] that assign importance to the three different best solutions of centre of mass, global best of PSO and a random number.

The hybrid algorithm also has two phases. The first phase, big bang phase has NP number of solutions spread over the search space. No change is introduced in this stage. The hybrid algorithm is similar to the original algorithm. In the second phase, centre of mass is identified and PSO is also activated. In this phase, in addition to knowing the centre of mass, the best of individual agents so far and best among the individual bests are considered. The new agents for the next iteration is created by using (16).

III.3 **HBB-BC Applied to ORPF:**

Step 1: Initialize the algorithm parameters like population size, maximum number of generations, particle best and global best.

Step 2: Each individual is a vector of the control variables. i.e. i.e. X_i= [V_{G1},V_{G2},…..V_{GNG},T_{P1},T_{P2},…..T_{PNT},Q_{c1},Q_{c2} ….Q_{cNC}]. NP number of agents are generated by respecting the limits of control parameters.

Step 3: Calculate the fitness function values of all candidates by running the NR load flow.

Step 4: Determine the centre of mass which has global best fitness using equation (15).

Step 5: Generate new candidates using the centre of mass, particle best and global best by adding/subtracting a normal random number according to equation (16).

Step 6: Repeat steps step 2 to step 5 until stopping criteria has been achieved.

IV. RESULTS AND DISCUSSIONS

The hybrid and basic versions of BB-BC are compared to prove the improved performance of the hybrid version. The effectiveness of the proposed algorithm is tested in the standard IEEE-30 bus system [20]. The algorithm is coded in MATLAB 7.6 Environment and a Core 2 Duo, 2.8 MHz, 2GB RAM based PC is for the simulation purpose.

The test system taken has six generating units connected to buses 1, 2, 5, 8, 11 and 13. There are 4 regulating transformers connected between bus numbers 6-9, 6-10, 4-12 and 27-28. Two shunt compensators are connected in bus numbers 10 and 24. The system is interconnected by 41 transmission lines. Therefore, the dimension of the problem is 12. The system is taken under base load condition.

Table 1. Control Variables and their limits.

Design Variable	Limit
Generator voltage (VG)	(0.9-1.1) p.u.
Tap setting (TP)	(0.9 -1.1) p.u.
MVAR by static compensators (QC)	(0-20) MVAR

Three different objective functions are considered to optimize the reactive power in the system. In case 'a' only real power loss is minimized, case 'b' considers optimization of voltage profile at the load buses and both real power loss and sum of voltage deviation are taken for reactive power optimization in case 'c'.

The optimal parameters of the algorithm in ORPD are: population size; 30, maximum number of iterations; 500, $\propto_1 = 0.03$, $\propto_2 = 0.04$, $\propto_3 = 0.06$. These three parameters assign due weights to the random number, size of centre of mass and size of global best solution respectively while deciding the size of new agents for the next iteration. It is found that the parameter values are the most suitable for the proposed work.

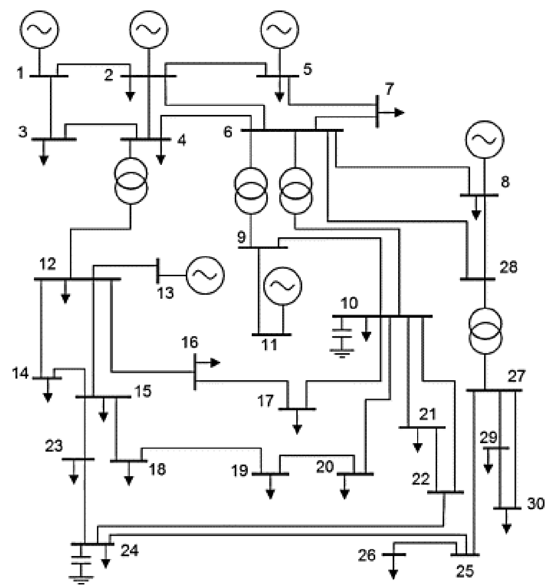

Figure 1. Single line diagram of standard IEEE -30 bus system.

IV.1 Case a: Minimization of Real Power Loss

The real power transmission loss minimization is the major component of reactive power optimization objective and it needs more attention. This case takes only the real power loss minimization as the objective function. The proposed algorithm is run and the optimal value of total line losses is obtained. Tuned values of control variables corresponding to minimal loss are given in table 2.

Table 2. Optimal parameter values (Case 'a')

S.No	Parameter	Initial value	Optimal value by HBB-BC	Optimal value by BB-BC
1	V_{G1}	1.05	1.1000	1.1000
2	V_{G2}	1.04	1.0906	1.0957
3	V_{G5}	1.01	1.0719	1.0760
4	V_{G8}	1.01	1.0802	1.0782
5	V_{G11}	1.05	1.0850	1.0495
6	V_{G13}	1.05	1.0674	1.1000
7	T_{6-9}	1.078	0.9813	1.0376
8	T_{6-10}	1.069	1.0999	0.9083
9	T_{4-12}	1.032	1.0537	0.9749
10	T_{27-28}	1.068	1.0498	0.9709
11	Q_{10}	0.0	6.9350	23.520
12	Q_{24}	0.0	11.3811	7.3395

It is clear from table 3 that HBB-BC algorithm

Parameter	Initial value	Real Power Loss Minimization	
		HBB-BC	BB-BC
P_{loss}	5.744	4.7754	4.807
VD	1.4753	0.8262	1.450

performs better than BB-BC in loss optimization. Sum of voltage deviation obtained by the hybrid algorithm is better. The loss minimization by the hybrid algorithm is 4.7754 against 4.804 got by the basic version of the algorithm.

Table 3. Minimization of objective terms (Case 'a')

For clear understanding of the improvement in voltage profile, the p.u. voltage magnitudes of all the buses in the system with HBB-BC and BB-BC algorithms are compared in figure 2. It is obvious from figure 2 that most of the load bus voltages are equal to about 1.0 p.u.

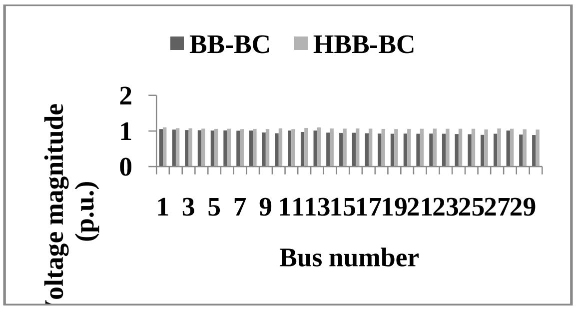

Figure 2. Voltage profile improvement (Case 'a')

The convergence efficiency of the hybrid algorithm is depicted in figure 3. Thealgorithm takes lessnumber of iterations and the global best results are retained.

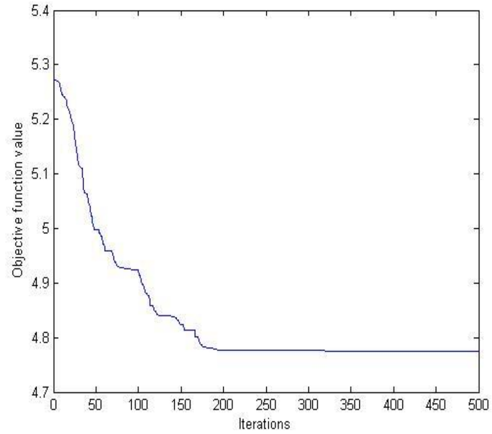

Figure 3. Convergence of HBB-BC (case 'a')

IV.2 Case b: Minimization of Sum of Voltage Deviation.

The objective of minimization of voltage deviation is considered in this case. The optimal settings of control variables that minimize the sum of voltage deviation are minimized by HBB-BC and BB-BC algorithms. Table 4 shows the control parameter values corresponding to objective function minimization using HBB-BC algorithm.

Table 4. Optimal parameter values (Case 'b')

S.No	Parameter	Initial value	Optimal value by HBB-BC	Optimal value by BB-BC
1	V_{G1}	1.05	0.9918	1.0200
2	V_{G2}	1.04	1.0584	1.0043
3	V_{G5}	1.01	1.0138	1.0290
4	V_{G8}	1.01	0.9794	1.0104
5	V_{G11}	1.05	1.0814	0.9896
6	V_{G13}	1.05	1.0564	1.0408
7	T_{6-9}	1.078	1.0740	0.9970
8	T_{6-10}	1.069	0.9772	0.9069
9	T_{4-12}	1.032	1.0042	1.0003
10	T_{27-28}	1.068	0.9306	0.9458
11	Q_{10}	0.0	10.7125	7.7001
12	Q_{24}	0.0	9.1656	10.8798

It is evident that the total voltage deviation was originally 1.475. It is reduced to 0.1794 by the proposed algorithm but it is 0.203 by the BB-BC algorithm. In this case, the hybrid algorithm outperforms the simple BB-BC algorithm. However, when the objective is only minimization of voltage deviation, the loss optimization is not acceptable

Table 5. Minimization of objective terms (Case 'b')

Parameter	Initial value	Voltage deviation Minimization	
		HBB-BC	**BB-BC**
VD	1.475	0.1794	0.203
P_{loss}	5.744	10.0754	5.551

As the objective is minimization of voltage deviation, the voltage at load buses is brought to about the nominal value. Figure 4 compares the voltages at different load buses after optimization by the algorithms.

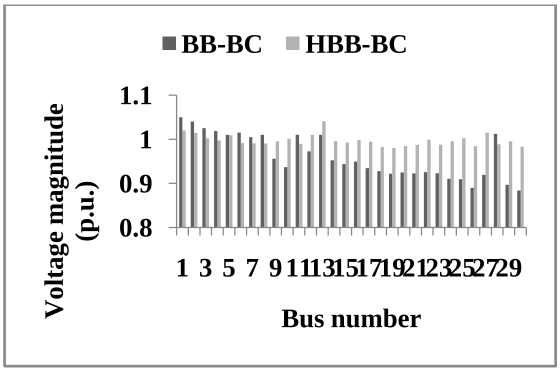

Figure 4. Voltage profile improvement (Case 'b')

Convergence capability of the HBB-BC is checked in this objective also. The algorithm founds to take slightly more number of iterations than what it took for loss optimization. But it is sticking to the best results remains well.

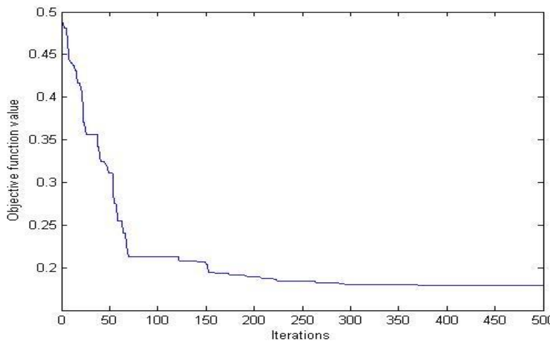

Figure 5. Convergence of HBB-BC (Case 'b')

IV.3 Case c: Minimization of Both Real Power Loss and Voltage Deviation.

Reactive power optimization by either loss minimization or VD minimization is not sufficient. Unlike the two previous cases, this case considers both real power loss and voltage deviation optimization simultaneously. This approach is most suitable for reactive power optimization as all the parameters of reactive power is included. Table 6 shows the optimal control parameters for minimization of both real power loss and voltage deviation

Table 6. Optimal parameter values (Case 'c')

S.No	Parameter	Initial value	Optimal value by HBB-BC	Optimal value by BB-BC
1	V_{G1}	1.05	1.0984	1.1000
2	V_{G2}	1.04	1.0898	1.0989
3	V_{G5}	1.01	1.0624	1.0740
4	V_{G8}	1.01	1.0640	1.0809
5	V_{G11}	1.05	1.0397	0.9759
6	V_{G13}	1.05	1.0756	1.0436
7	T_{6-9}	1.078	1.0386	1.0791
8	T_{6-10}	1.069	1.0385	1.0140
9	T_{4-12}	1.032	1.0852	1.0958
10	T_{27-28}	1.068	1.0200	1.0576
11	Q_{10}	0.0	9.0424	23.2942
12	Q_{24}	0.0	9.3153	9.0131

The two objective terms of loss and voltage deviation are optimized by the algorithm suggested. HBB-BC minimizes both the real power loss and VD in a better way. It is evident from the table 7 that the results obtained by the hybrid algorithm are really good.

Table 7. Minimization of objective terms (Case 'c')

Parameter	Initial value	Both Real Power Loss & Voltage Deviation Minimization	
		HBB-BC	**BB-BC**
P_{loss}	5.744	4.8133	4.821
VD	1.4753	0.5554	0.602

The improvement in voltage profile at the buses of the system using HBB-BC algorithm and BB-BC algorithm are compared in figure 6. It is clear from the diagram that the VD minimization by the HBB-BC is better than that by the BB-BC algorithm.

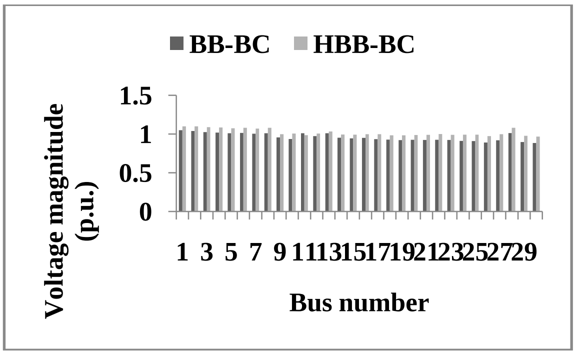

Figure 6. Voltage profile improvement (Case 'c')

The algorithm takes the lowest number of iterations in this case than in the two previous cases. The objectives optimized are the loss and VD. Hence it may be noted that this algorithm retains its strength even when two objective terms are considered. The algorithm converges to the global best results in an augmented multi objective problem.

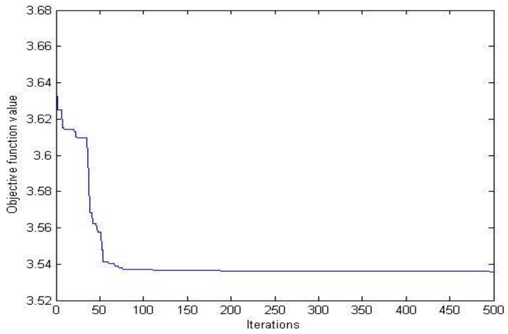

Figure 7. Convergence of HBB-BC (Case 'c')

V. CONCLUSIONS

In this paper, the strength of the hybrid version of BB-BC algorithm is demonstrated. The simple and easy to implement algorithm is enhanced by hybridization with PSO and successfully applied for power system optimization. The exploration capability of the basic BB-BC algorithm is improved by combining the exploration quality of PSO. The HBB-BC is an enhanced version of BB-BC and has good exploitation and exploration capabilities. This ensures the strength of the proposed algorithm in both local search and global search. The numerical results show that the hybrid version of the algorithm outperforms its basic form. Three different objectives are considered for verifying the effectiveness. In all the three objectives the performance is better. Further, optimization of reactive power by the proposed algorithm is highly encouraging. Moreover, the total Var requirement suggested by HBB-BC is much smaller against the one recommended by the basic algorithm. The reduction in Var requirement is equivalent to maximization of Var reserves in a power system. Therefore, the proposed algorithm in addition to reactive power optimization maximizes the Var reserves. The algorithm may be used for other power system optimization works like economic load dispatch, optimal power flow and voltage stability improvement.

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