Journal of Theoretical and Applied Information Technology
20th January 2013. Vol. 47 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID BIG BANG–BIG CRUNCH OPTIMIZATION BASED OPTIMAL REACTIVE POWER DISPATCH FOR VOLTAGE STABILITY ENHANCEMENT

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ABSTRACT

One of the most crucial functions in the operation and control of power system is reactive power dispatch (RPD).A hybrid Big Bang–Big Crunch (HBB–BC) optimization algorithm which consists of A Big Bang–Big Crunch algorithm combined with particle swarm optimization (PSO) is proposed in this paper in order to solve optimal reactive power dispatch (ORPD) problem. The L-index of load buses is base for the monitoring methodology for voltage stability. Minimizing the real power loss is the objective. This algorithm is used to find the settings of control variables such as generator voltages, tap positions of tap changing transformers and switchable VAR sources. Furthermore, the optimization models are implemented and solved using the GAMS programming language .The proposed method has been carried out on IEEE 30 -bus test system. For comparative study the results obtained by the proposed algorithm are compared with those obtained by modeling the optimization problem in the GAMS environment. The outcomes indicate that the real power loss is decreased with voltage stability margins increased simultaneously.

Keywords: *Particle Swarm Optimization, Reactive Power Dispatch, Voltage Stability ,Big Bang–Big Crunch Algorithm, L-Index*

1. INTRODUCTION

Nowadays, reactive power optimization plays a vital role in optimal operation of power systems. There have been many papers by different authors proposed to solve the RPD problem such as Newton approach, linear programming, and interior point methods. Thanks to significant improvement in computers' capability in recent years, The expert systems [7], fuzzy logic [8], AI approach [9], fuzzy linear programming [10]evolutionary computation techniques such as Genetic Algorithm (GA) [11], Evolutionary Programming (EP) [12] and Evolutionary Strategy [13] have been applied for solving various complex ORPF problems. Increasingly, a major concern in planning and operation of present day power systems is voltage stability. With unmatched generation and transmission capacity expansion, this problem has become very complex due to the continuous growth in the demand for electricity. Stressed system operating at a higher loading condition could often cause voltage instability. In such operating conditions some of the system parameters will be operating close to their limits and these parameters by following contingencies such as unexpected line outages will violate the system limits, which may lead to voltage collapse. The inability of the power system to meet the demand for reactive power to maintain normal voltage profiles in stressed situations is the main factor causing voltage collapse. Vaisakh and P. Kanta Rao [14] present a Differential Evolution (DE)- based approach for solving optimal reactive power dispatch including voltage stability limit in power systems. The monitoring methodology for voltage stability is based on the L-index[15] of load buses. For voltage stability enhancement based on the minimization of the maximum of L-indices, an improved Genetic algorithm (GA) approach is suggested in [16]. This study proposes a novel optimization method that relies on one of the theories of the evolution of the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

universe; namely, the Big Bang and Big Crunch Theory [17]. According to this theory in the Big Bang phase; energy dissipation yields disorder and randomness; while, in the Big Crunch phase, randomly distributed particles are brought back into an order. Motivated by this theory, an optimization algorithm is assembled, which will be called the Big Bang–Big Crunch (BB–BC) method that generates random points in the Big Bang phase and reduces those points to a single representative point through a center of mass or minimization of cost approach in the Big Crunch phase. For improving performance of BB–BC, a hybrid Big Bang–Big Crunch optimization (HBB–BC) is implemented to solve optimization problem. HBB–BC is based on the BB–BC optimization method and the particle swarm optimization (PSO) [18]. The HBB–BC not only considers the center of mass as the average point in the beginning of each Big Bang, but also similar to the approach in particle swarm optimization, utilizes the best position for each particle and the best visited position for all particles. Therefore it causes the performance of the BB–BC approach to improve because of expanding exploration of the algorithm [19]. These unique properties of this novel algorithm encouraged the authors to utilize this method to solve ORPF problems where the purpose is to minimize an objective function which is the real power loss. This algorithm is applied to obtain the optimal control variables so as to improve the voltage stability level of the system in normal and contingency state. The performance of the proposed method has been tested on IEEE 30 bus system. Observations suggest that the proposed method can work more efficiently in both cases, when compared to result obtained by modeling the problem in GAMS environment. This paper is organized as follows: Section 2 introduced voltage stability index. Section 3 provides a concise description and mathematical formulation of ORPF problems. The HBB–BC approach is described in Section 4 together with a short description of the algorithms. Section5 describe implementation of (HBB–BC) in the ORPD problem. Simulation results are presented for different cases in section 6. Finally the General conclusions are drawn in section 7.

2. VOLTAGE STABILITY INDEX

The voltage stability analysis of a power system can be determined by an index of quantifiable voltage stability, there are a variety of indexes that help assess the steady state voltage stability. In our case, the voltage stability index (L-index) is used [15]. It is based on a load flow analysis and varies in the range between 0 (for no load) to 1 (voltage collapse point).This index is able to evaluate the steady state voltage stability margin of each bus. The bus with the highest L-index value will be the most vulnerable. The L-index calculation for a power system is briefly discussed as follows: If a power system has N number of total bus, $N_G$number of PV bus and N_L number of load bus, then the relationship between voltage and current may be represented as:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \quad (1)$$

WhereV_L, I_L are the voltage and current at the load buses.
V_G, I_G are the voltage and current vectors at the generator buses.
Rearranging Eq. (1) we obtain

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (2)$$

Where

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}] \quad (3)$$

The L-indices for a given load condition are computed for all load buses. The equation for the L-index for *j*-th node can be written as:

$$L_j = \left| 1 - \sum_{i=1}^{NG} |F_{ji}| \frac{|V_i|}{|V_j|} \angle(\Theta_{ij} + \delta_i - \delta_j) \right| \quad (4)$$

$$F_{ji} = |F_{ji}| \angle \Theta_{ij} \quad (5)$$

$$V_i = |V_i| \angle \delta_i \quad (6)$$

$$V_j = |V_j| \angle \delta_j \quad (7)$$

The values of $F_{ji}$are obtained from the matrix F_{LG} .The L-index of a bus indicates the proximity of voltage collapse condition of that bus. The indicator $L_{max}$is used to estimate the distance of the actual state of the system to the stability limit and considered to be a quantitative measure.

3. PROBLEM FORMULATION

To improve voltage stability margin, this paper presents an algorithm for reactive power

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

optimization in which case, the objective is to minimize the real power loss. While satisfying equality and inequality constraints, the function is optimized. This is mathematically is represented as follows:

$$P_{Loss} = \sum_{i,j \in N} G_{i,j}(U_i^2 + U_j^2 - 2U_i\ U_j \cos(\theta_{ij})) \quad (8)$$

The reactive power optimization problem is subject to the following constraints:

Equality Constraints

The equality constraints are the balance of the active and reactive power described by the set of power flow equations, and are satisfied by running the power flow program. They can be expressed as follows:

$$\text{(i)} P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} V_j(G_{ij}\cos(\theta_{ij}) + B_{ij}\sin(\theta_{ij}))$$
$$i = 1,2, \ldots \ldots \ldots N_{B-1} \quad (9)$$

$$\text{(ii)} Q_{Gi} - Q_{Di} = V_i \sum_{j \in N_i} V_j\ (G_{ij}\sin(\theta_{ij}) - B_{ij}\cos(\theta_{ij}))$$
$$i = 1,2, \ldots \ldots . . N_{PQ} \quad (10)$$

Where N_{PQ} andN_{B-1}, are number of load buses and total number of buses excluding slack bus respectively; $P_G$and Q_G are the generator real and reactive power respectively; $P_D$and Q_D are the load real and reactive power respectively; Gij and Bij are the transfer conductance and susceptance between bus i and bus j respectively.

Inequality Constraints
The inequality constraints in all of the problems represent the system operating constraints. Generator terminal bus voltages, transformers tap setting, and reactive power generated by the capacitor bank are the control variables which are self – constrained. Voltage stability index of load buses, reactive power generation, load bus voltages, and line flow limit are the state variables whose limit is satisfied in the objective function by penalty coefficients.

(iii) Generator voltages (V_G) and reactive power outputs (Q_G) are restricted by their limits as follows:

$$Q_{Gi\,min} \leq Q_{Gi} \leq Q_{Gi\,max} \quad i \in N_{PV} \quad (11)$$

$$V_{Gi\,min} \leq V_{Gi} \leq V_{Gi\,max} \quad i \in N_{PV} \quad (12)$$

Where, N_{PV} is number of voltage buses.

(iiii) Load Bus Voltage (VL):

$$V_{Li\,min} \leq V_{Li} \leq V_{Li\,max} \quad i \in N_{PQ} \quad (13)$$

Where, N_{PQ} is the number of load buses.

(v) Capacitor bank reactive power is limited as follows:

$$Q_{Cimin} \leq Q_{Ci} \leq Q_{Ci\,max} \quad i \in N_C \quad (14)$$

Where, NC is the number of capacitor banks.

(vi) Tap settings are restricted as:

$$t_{k\,min} \leq t_k \leq t_{k\,max} \quad i \in N_T \quad (15)$$

Where, N_T is the number of tap-setting transformer branches.

(vii) Line flow limited as follows:

$$S_l \leq S_l^{max} \quad l \in N_L \quad (16)$$

Where, N_L is the number of transmission lines.

(viii) Voltage stability constraint:

$$L_j \leq L_{max} \quad j \in N_{PQ} \quad (17)$$

Where, N_{PQ} is the number of load buses.

The next section presents the details of proposed approach for solving this particular complex optimization problem.

4. HBB–BC METHOD APPROACHES

4.1. BB–BC

The BB–BC method developed by Erol and Eksin [17] consists of two phases: a Big Bang phase, and a Big Crunch phase. In the Big Bang phase, candidate solutions are randomly distributed over the search space. Erol and Eksin [17] related the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a chaos state (new set of solution candidates).The Big Ban phase is followed by the Big Crunch which is a convergence operator which includes many inputs but only one output Known as the ‘‘center of mass”. The only outcome has been achieved by calculating the center of mass. In here, the term mass refers to the inverse of the fitness function value as mentioned in [20]. The point representing the center of mass is also represented by $x^c$and is calculated by

$$\vec{x}^c = \frac{\sum_{i=1}^{N}\frac{1}{f^i}\vec{x}^i}{\sum_{i=1}^{N}\frac{1}{f^i}} \quad (18)$$

Where $x^i$is a point generated within an n-dimensional search space, $f^i$is a fitness function value of this point, and N is the population size in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the Big Bang phase. After the Big Crunch phase, the algorithm must create new members to be used as the Big Bang of the next iteration step which can be done by utilizing the previous knowledge (center of mass) by spreading new off-springs around this center of mass using a normal distribution operation in every direction where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases [20]

$$x^{\mathrm{new}} = x^{\mathrm{c}} + \frac{\mathrm{l.r}}{\mathrm{k}} \quad (19)$$

Where x^{c}stands for the center of mass, l is the upper limit of the parameter, r is a normal random number and k is the iteration step. Then new point x^{new} is upper and lower bounded. The center of mass is recalculated after the second explosion. These consecutive explosion and contraction steps are carried repetitively until a stopping criterion has been met.

4. 2. HBB–BC

In order to improve the exploration ability, this paper uses the potentials of the particle swarm optimization to improve the ability to explore the BB–BC algorithm. The particle swarm optimization is inspired by the social behavior of bird flocking and fish schooling that has a population of individuals, called particles, which sets their movements depending on their own experience as well as the population's experience [18]. In every iteration, a particle travels towards a direction which is computed from the best visited position (local best) and also the best visited position of all particles in its neighborhood (global best). The HBB–BC method not only uses the center of mass but also utilizes the best position of each candidate ($pbest_i$) as well as the best global position ($gbest_i$) to produce a new solution [20],

$$x_{\mathrm{i}}^{\mathrm{new(k+1)}} = \alpha_2 x_{\mathrm{i}}^{\mathrm{c(k)}} + (1-\alpha_2)(\alpha_3 gbest_i^k + (1-\alpha_3\ )pbest_i^k) + \frac{r\alpha_1(x^{\max}-x^{\min})}{\mathrm{k}+1} \quad (20)$$

Where $r_j$is a random number from a standard normal distribution that changes for each candidate, and $\alpha_1$is a parameter for limiting the size of the search space.α2 and α3 are adjustable parameters controlling the influence of the global best and local best on the new position of the candidates, respectively. The agent of a population-based search algorithm performs three steps in every iteration to achieve the concepts of exploration and exploitation: self-adaptation, cooperation and competition. In is noteworthy to mention that in the self-adaptation step, each particle improves its performance. In the cooperation step, members cooperate with each other by transforming the information. Finally, in the competition stage, members try to compete in order to survive. In the standard BB–BC algorithm, although the cooperation step is satisfied by using the concept of center of mass, the self-adaptation and cooperation steps are not considered to be suitable enough. Adding the potentials of the PSO algorithm will definitely improve these steps. The first term of Eq. (20) represents the cooperation step of the algorithm. The term related to $pbest_i$can be considered as the self-adaptation step of the algorithm that incites particles to improve their solutions, and the competition step is shown by the term related to $gbest_i$. Ultimately, the stochastic form of the algorithm is incorporated by using the last term in the Eq. (20).

5. IMPLEMENTION OF HBB–BC IN THE ORPD PROBLEM

The implementation of the proposed algorithms for the optimization problem must first include finding the optimal value of control variables namely, generator bus voltages ($\mathrm{V_{Gi}}$), second the transformer tap-setting ($\mathrm{t_k}$), and finally the reactive power generation ($\mathrm{Q_{Ci}}$) to minimize the object function while handling the constraints. The implementation process of HBB–BC to the optimal reactive/voltage control problem is described as follows:

Fitness Function: In the reactive power optimization problem under consideration, the objective is to minimize real power loss, satisfying the constraints given by equations (11) to (17). For each particle, the equality constraints given by equations (9) and (10) are satisfied by running Newton-Raphson algorithm. Moreover, the inequality constraints on the control variables are considered in the problem representation itself and the constraints on the state variables are considered by adding a quadratic penalty function to the objective function. With the inclusion of penalty function, the new objective function then becomes:

$$\mathrm{Minf} = P_{Loss} + \mathrm{K_L}\sum_{\mathrm{j=1}}^{\mathrm{N_{PQ}}} \Delta\mathrm{L_{Lj}}^2 + \mathrm{K_v}\sum_{\mathrm{j=1}}^{\mathrm{N_{PQ}}} \Delta\mathrm{V_{Lj}}^2 + \mathrm{K_q}\sum_{\mathrm{j=1}}^{\mathrm{N_g}} \Delta\mathrm{Q_{Gj}}^2$$

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$+ K_F \sum_{j=1}^{N_L} \Delta S_{Lj}^{\ 2} \qquad (25)$$

where K_L, K_v , K_q and K_F are the penalty factors for voltage stability limit violation, the load bus voltage limit violation, generator reactive power limit violation, and the line flow violation respectively. In the above objective function ΔL_{Lj} , ΔV_{Lj}, ΔQ_{Gj}, ΔS_{Lj} are defined as:

$$\Delta L_{Lj} = \begin{cases} L_{Lj} - L_{Lj}^{max} & \text{if } L_{Lj} > L_{Lj}^{max} \\ 0 & \text{otherwise} \end{cases} \qquad (26)$$

$$\Delta V_{Lj} = \begin{cases} V_{Lj} - V_{Lj}^{max} & \text{if } V_{Lj} > V_{Lj}^{max} \\ V_{Lj}^{min} - V_{Lj} & \text{if } V_{Lj} < V_{Lj}^{min} \\ 0 & \text{otherwise} \end{cases} \qquad (27)$$

$$\Delta Q_{Gj} = \begin{cases} Q_{Gj} - Q_{Gj}^{max} & \text{if } Q_{Gj} > Q_{Gj}^{max} \\ Q_{jG}^{min} - Q_{Gj} & \text{if } Q_{Gj} < Q_{Gj}^{min} \\ 0 & \text{otherwise} \end{cases} \qquad (28)$$

$$\Delta S_{Lj} = \begin{cases} S_{Lj} - S_{j}^{max} & \text{if } S_{Lj} > S_{Lj}^{max} \\ 0 & \text{otherwise} \end{cases} \qquad (29)$$

The HBB–BC approach takes the following steps:

Step 1: Form initial candidates in a randomly. Respect the limits of the search space.

Step 2: By running Newton-Raphson power flow, calculate the fitness values of all the candidate solutions

Step 3: According to (18), find the center of the mass. Best fitness individual can be chosen as the center of mass.

Step 4: According to (20), calculate new candidates around the center of the mass

Step 5:Return to step 2 until a stopping criterion is reached.

6. SIMULATION RESULTS

HBB–BC has been implemented to IEEE 30-bus which is shown in Fig.1. These systems are optimized using the optimal reactive power dispatch method for normal and contingency states for two cases, the first is under base load condition for 100 % load level and the second one is under 125% load level with the incorporation of the voltage stability limit in both the cases. Simulation performed in MATLAB-7. Also this NLP problems are modeled in GAMS-23.5 [21] and solved using the SNOPT [22] solver.

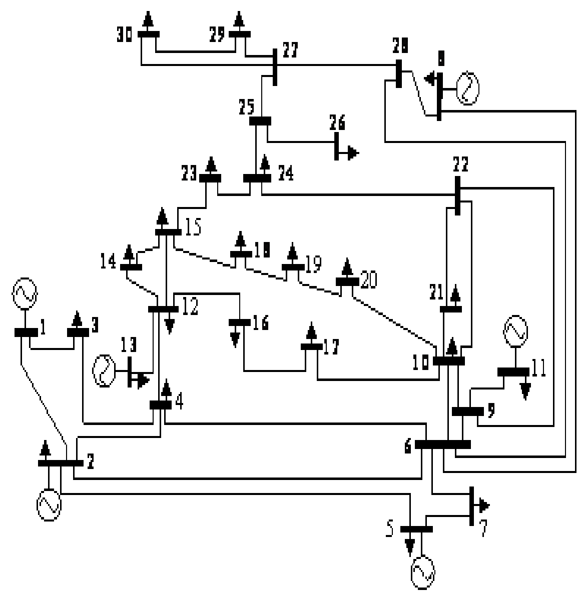

Fig.1. IEEE 30 Bus System.

The IEEE 30-bus network used in this study consists of 6 generators, 24 load buses and 41 transmission lines of which 4 branches (i.e., 6-9, 6-10, 4-12, and 28-27) are with tap setting transformers. The system data of this power system are available in [23]. Tap settings are in the range of 0.9-1.1. The reactive compensation devices are considered within the interval 0-15 Mvar. Also the voltages of all bus buses except the slack bus are limited to 0.9-1.1 p.u. The slack bus bar voltage is fixed to its specified value of 1.06 p.u. For the proposed algorithm, a population of 30 individuals is used for all the examples. Also, maximum iteration number is set to be at 60. The value of the constants α_1, α_2 and α_3 are set to 1.0, 0.95 and 0.68, respectively. The base power value is 100 MW. For the ORPD problem, the candidate buses for reactive power compensation are 10, 12, 15, 17, 20, 21, 23, 24 and 29.

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6.1.case1(100% load level)

First to obtain the optimal values of the control variables the HBB-BC algorithm was run for the 100 % load level. In this case, the objective is to minimize the real power loss that is calculated to be $P_{Loss} = 0.1755$. By calculating L-index it is found that $L_{max} = 0.1435$ .Also The optimum settings of the control variables, power loss and L_{max} for this purpose as obtained from the HBB-BC method and modeling of the problem in GAMS solver are given in Table 1 and Table 2.

Table 1: Controller settings under base cases for IEEE 30- bus system(case1)

Method	***HBB-BC***		
V_1	1.06	Q_{20}	0.340
V_2	1.0179	Q_{21}	0.078
V_5	1.0269	Q_{23}	0.018
V_8	0.9882	Q_{24}	0.035
V_{11}	1.0189	Q_{29}	0.026
V_{13}	1.0190	t_{6-9}	1.0010
Q_{10}	0.016	t_{6-10}	1.0323
Q_{12}	0.105	t_{4-12}	0.9822
Q_{15}	0.047	t_{28-27}	0.9759
Q_{17}	0.084		
P_{Loss}	0.1171		
L_{max}	0.1139		

It is clear from Table1 and Table 2 that The minimum transmission loss achieved using HBB–BC is 0.1171 which is less in comparison to the result obtained with GAMS solver . The objective function (Ploss) are plotted against the number of iterations in Fig. 2. As depicted in this figure one can readily see the proposed algorithm converges rapidly towards the optimal solution

The voltage profile of the system before and after the application of the HBB–BC algorithm is presented in Fig. 3.Improvement in the voltage profile of the system after the application of the algorithm is evident from this figure.

Table 2: Controller settings under base cases for IEEE 30- bus system(case1)

Modeling with GAMS			
V_1	1.06	Q_{20}	0.043
V_2	1.045	Q_{21}	0.115
V_5	1.013	Q_{23}	0.016
V_8	1.019	Q_{24}	0.029
V_{11}	1.0189	Q_{29}	0
V_{13}	1.100	t_{6-9}	0.982
Q_{10}	0	t_{6-10}	0.982
Q_{12}	0	t_{4-12}	0.948
Q_{15}	0.068	t_{28-27}	0.928
Q_{17}	0.080		
P_{Loss}	0.173		
L_{max}	0.114		

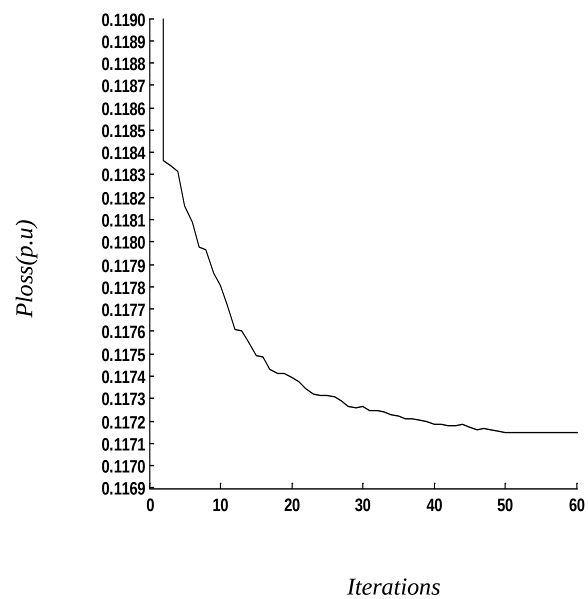

Fig.2.Objective Function Value Vs Iterations For Case 1

Journal of Theoretical and Applied Information Technology
20th January 2013. Vol. 47 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

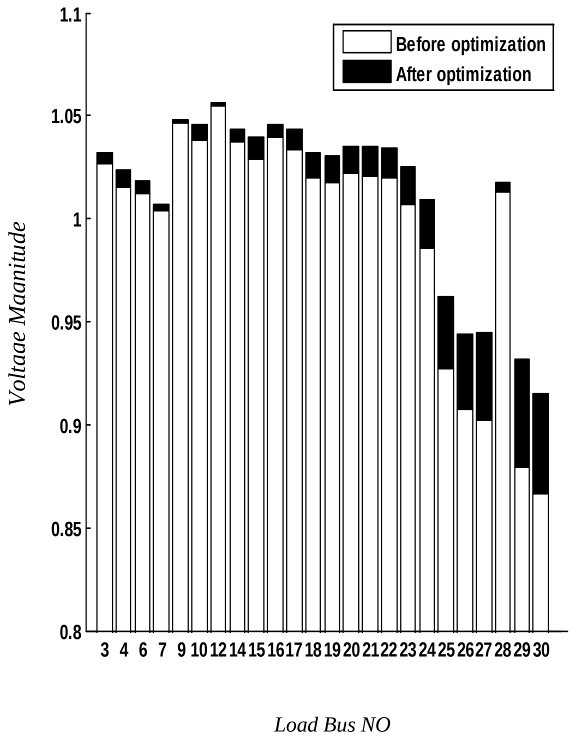

Fig. 3. Voltage Profile For Case 1 (Base Case).

To investigate the system under disturbance, contingency analysis was conducted. From the contingency analysis, the most severe case is found for line outages (28–27). For these optimal values of control variables Table 3 show the system performance before and after the application of the HBB-BC method when line (28–27) was removed.

Table3: Performance Parameters for IEEE 30- bus system (Line outage(28–27) for case 1)

HBB-BC		
Before optimization		
P_{Loss}	L_{max}	V_{min}
0.1943	0.3762	0.866
After optimization		
P_{Loss}	L_{max}	V_{min}
0.1937	0.2939	0.922

By calculating L-index by using optimal values of control variables obtained with GAMS solver it is found that $L_{max} = 0.318$. From Tables 3, it is found that the value of ploss and L_{max} decreased and voltage stability has improved after the application of the algorithm. The voltage profile of the system before and after the application of the HBB–BC algorithm under contingency (28–27) is presented in Fig. 4. As it is seen in this figure the voltage profile is improved.

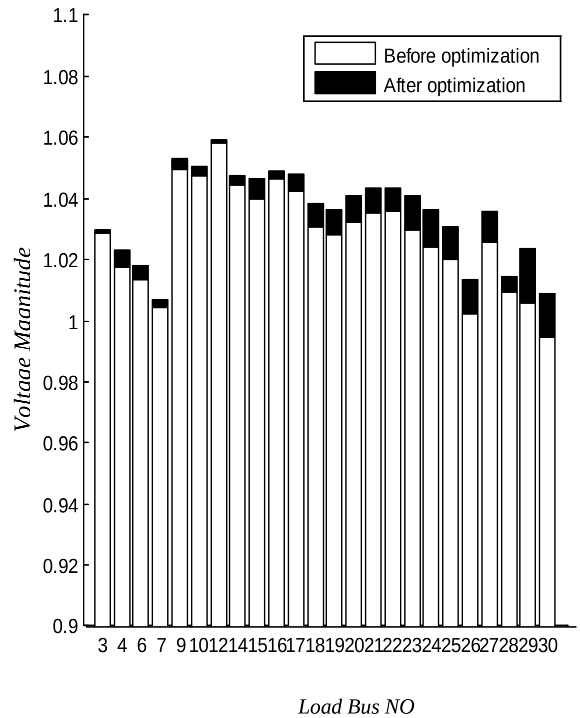

Fig.4. Voltage Profile Under Line Outage 28-27 For Case 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6.1.Case2 (125% load level)

In this case by calculating L-index and the real power loss for the 125 % load level it is found that $L_{max} = 0.1884$ and $P_{Loss} = 0.2935$.So HBB-BC algorithm implemented for minimizing power loss and voltage stability index. Optimum settings of the control variables, power loss and L_{max} for this purpose as obtained from the HBB-BC method and modeling of the problem in GAMS solver are given in Table 4 and Table 5.

Table 4: Controller settings under base case for IEEE 30- bus system(case2)

Method	***HBB-BC***		
V_1	1.06	Q_{20}	0.050
V_2	1.0092	Q_{21}	0.114
V_5	1.0309	Q_{23}	0.019
V_8	0.9860	Q_{24}	0.059
V_{11}	1.0073	Q_{29}	0.039
V_{13}	1.0029	t_{6-9}	1.0031
Q_{10}	0.031	t_{6-10}	1.0236
Q_{12}	0.136	t_{4-12}	0.9790
Q_{15}	0.072	t_{28-27}	0.9688
Q_{17}	0.079		
P_{Loss}	0.1912		
L_{max}	0.1497		

As seen in Table4 and Table 5 by using HBB–BC algorithm the minimum transmission loss is 0.1912 which is less in comparison to the result obtained with GAMS solver . Also in this case the objective function (Ploss) are plotted against the number of iterations in Fig. 5. As the figure shows, the proposed algorithm converges towards the optimal solution pretty quickly, which an indication of the its efficacy for ORPD problem.AlsoFig.6 illustrates the improvement in the voltage profile of the system after the application of HBB-BC algorithm.

Table 5: Controller settings under base case for IEEE 30- bus system(case2)

Modeling with GAMS			
V_1	1.06	Q_{20}	0.063
V_2	1.038	Q_{21}	0.178
V_5	0.977	Q_{23}	0.020
V_8	1.014	Q_{24}	0.054
V_{11}	1.100	Q_{29}	0.039
V_{13}	1.100	t_{6-9}	1.035
Q_{10}	0	t_{6-10}	0.988
Q_{12}	0	t_{4-12}	0.979
Q_{15}	0.103	t_{28-27}	0.932
Q_{17}	0.133		
P_{Loss}	0.287		
L_{max}	0.150		

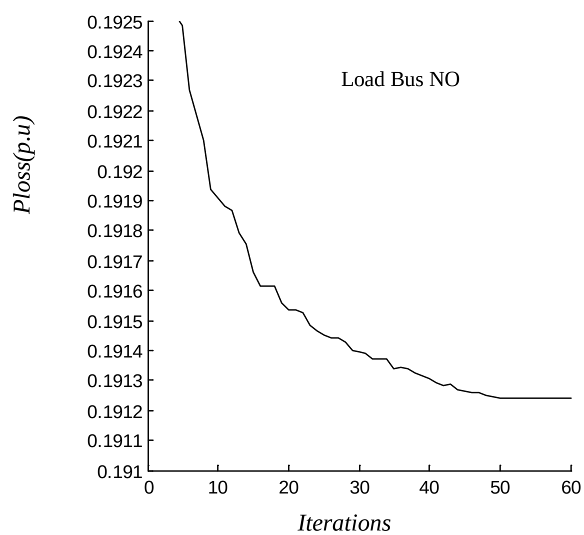

Fig.5.Objective Function Value Vs Iterations For Case 2

Journal of Theoretical and Applied Information Technology
20th January 2013. Vol. 47 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

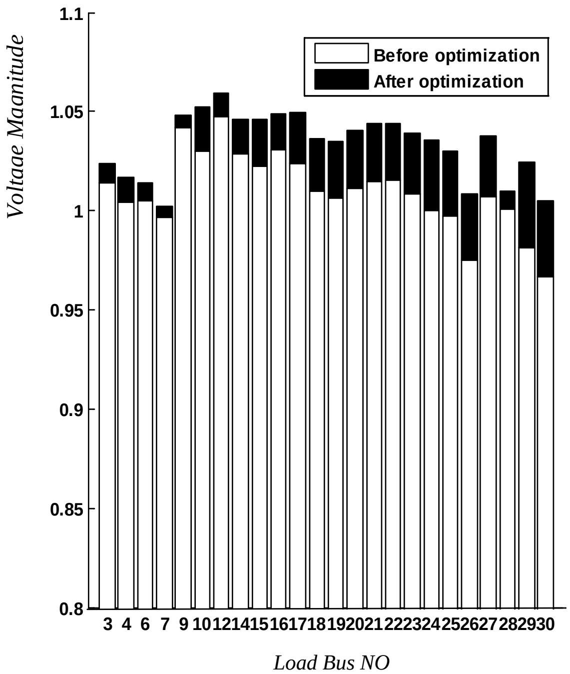

Fig. 6. Voltage profile for case 2(base case) .

Table 6: Performance Parameters for IEEE 30- bus system (Line outage(28–27)for case2)

HBB-BC		
Before optimization		
P_{Loss}	L_{max}	V_{min}
0.3409	0.5828	0.7669
After optimization		
P_{Loss}	L_{max}	V_{min}
0.3282	0.3915	0.8759

Again a network contingency is considered in this system. From the contingency analysis, the most severe case is found for line outages (28–27).For optimal values of control variables with GAMS solver it is found that $L_{max} = 0.4250$. As indicated in Table 6 by using the proposed algorithm when line (28–27) was removed, improvement in voltage stability was achieved and also the value of ploss and L_{max} decreased.

Figure 7 show the voltage profile of the system before and after the application of the HBB–BC algorithm under contingency (28–27). As it is evident in this figure there is an improvement in the voltage profile.

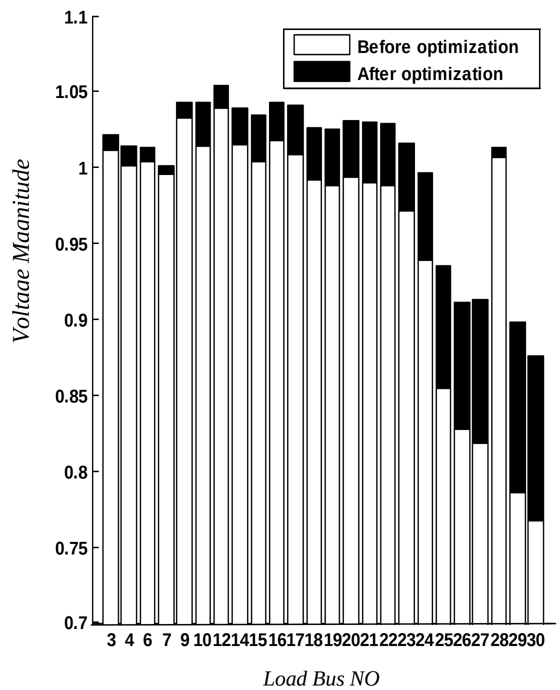

Fig.7. Voltage Profile Under Line Outage 28-27 For Case 2

7. CONCLUSIONS

In this paper, the HBB–BC has been successfully implemented to solve ORPF problems. The proposed hybrid BB–BC algorithm considers the combination of the center of mass, the best position of each candidate and the best visited position of all candidates as an average point in the beginning of each Big Bang. The simulation results on IEEE 30-bus test system demonstrate the proposed algorithm is able to improve voltage stability condition along with loss minimization in the normal and contingency situations. The comparison of numerical results of optimal reactive power flow (ORPF) problems with the results obtained by modeling in the GAMS environment, demonstrates the ability of convergence to a better quality solution and possession of superior convergence characteristics of the studied algorithms. These algorithms are demonstrated to give encouraging results for base case and credible contingency conditions.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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