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Multiobjective Generation Dispatch using Big-Bang and Big-Crunch (BB-BC) Optimization

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Abstract

Big – Bang and Big – Crunch (BB-BC) optimization method for multioptimization of economic load dispatch and emission dispatch of thermal power generating stations is presented using weighted sum method, trade-off solutions are obtained assuming decision makers (DM) requirements by solving optimal power flows. BB-BC optimization which is a non- derivative, population search optimization procedure developed based on Universal Evolution, is simple to code and fast optimization method trade-off (pareto) solution obtained by BB-BC is compared with well researched most popular PARTICLE SWARM OPTIMIZATION for two typical power system networks, IEEE-25(Gangour) and IEEE-30 bus systems. Outcome of comparison suggests that BB-BC optimization solutions are as superior as PSO

Keywords: multiobjective, Big-Bang-Crunch optimization trade-off (Pareto).

Introduction

Multiobjective optimization in power systems is to obtain multiple Non-inferior solutions for steady state and dynamic operating conditions of power system so that Decision Maker (DM) can select one of the best options for power system operation. Multiobjective optimization in power system can be obtained for cost minimization of thermal emission, voltage deviations, power line thermal limits etc. Minimization of these functions has to be done by satisfying various equality, in-equality and operational constraints of the power system. Real and reactive power optimization are carried out by energy computing centres to arrive at best settings of generator out puts, specified voltages of the generators, ratings and control settings of power system compensating devices[1,2]. Now-a-days, due to increased public awareness of environmental protection and stringent rules by pollution control boards, many researchers explored the optimization of power system network for combined economic/ emission power dispatch [3]. Assuming thermal power generation (which contribute major electric power to the grid), creates thermal emission such as N_{OX},S_{OX} and $C_{O2,}$ inclusion of these emissions along with cost function leads to multiobjective optimization. It is well known fact that there exists a trade-off between cost of power generation and Emission of pollution. DM of energy control system has to depend on multiobjective optimization to decide the settings of the power generator. Many researchers investigated various traditional [4] and non-traditional optimization methods to obtain reliable and fast trade-off solutions.

Non-traditional optimization methods such as Genetic Algorithms and their variants [5], Simulated Annealing [6], Particle Swarm Optimization (PSO) [7], etc with various modifications are successfully applied to obtain trade-off solutions. These methods may be considered as non-classical, unorthodox and stochastic search optimization algorithms, known as Evolutionary Algorithms (EA). EA use a population of solutions in each iteration instead of a single solution. If an optimization problem has multiple optimal solutions, EA can be used to capture multiple optimal solutions in its final population. This ability of population based optimization methods to find multiple optimal solutions in one single simulation run makes these methods unique in solving multiobjective optimization problems. Evolutionary Methods are particularly required when function to be optimized is discontinuous such as ramp cost functions with valve point loading [8].

Among stochastic search methods, PSO has gained utmost popularity for many optimization problems of power system due its simple code and ability to tune both for local and global search in solution space[9].To the list of non-traditional methods, the recent contribution of Optimization method is Big Bang- and Big-Crunch(BB-BC), developed by Erol and Eksin [10] . This optimization is based on the concept of universal evolution. According to this theory, in the Big Bang phase, energy dissipation produces disorder and randomness. In the Big Crunch phase, randomly distributed particles are drawn into an order. The Big Bang–Big Crunch (BB–BC) Optimization method similarly generates random points in the Big Bang phase and shrinks (draw) these points to a single representative point via a centre of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB–BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions [11]. In this paper an effort is made to compare trade -off solution between economic power dispatch and emission dispatch (multiobjective optimization) by thermal power stations by BB-BC and PSO.

To compare the two optimization methods two practical power system networks IEEE-25bus test system (Gangour), standard IEEE-30 bus test system are considered to obtain trade-off Solution between cost of power generation minimization and thermal emission. BB-BC trade off solutions are compared with PSO trade-off solutions. The outcome of the comparison clearly indicates the effectiveness of BB-BC optimization for trade-off solutions of power systems.

This paper is organized as follows: section2 presents an overview of multiobjective optimization. In Section3, multiobjective formulation of minimum cost dispatch and minimum emission dispatch along with weighted sum formulation of combined function is presented. In Section 4, optimization concept of BB (Big Bang) phase and BC (Big Crunch),is explained. Like all EA optimizations, BB-BC is also unconstrained optimization; hence, Section V deals with tackling of constraints of power system in optimization function and also explains the BB-BC algorithm. Results are discussed in section 6, along with test cases Considered for simulation. Conclusions are made in Section 7.

Multiobjective optimization

Engineering design often deals with multiple, possibly conflicting, objective functions or design criteria. As an example, one may want to maximize the performance of a system while minimizing its cost. Such design problems are the subject of multiobjective optimization and can generally be formulated as:

$$
\begin{aligned}
&\min J(x,p) \\
&\text{subject to } g(x,p) \leq 0 \\
&h(x,p) = 0 \\
&J=[J_1(x),,\ldots\ldots J_z(x)]\ T \\
&x=[x_1,,\ldots\ldots x_n]T \qquad (1)\\
&g=[g_1(x),\ldots\ldots g_{m1}(x)]\ T \\
&h=[h_1(x)\ldots\ldots h_{m2}(x)]\ T
\end{aligned}
$$

In equation (1), J is an objective function vector, x is a design vector, p is a vector of fixed parameters, g is an inequality constraint vector and h is an equality constraint vector. There are z objectives, m1 inequality constraints and m2 equality constraints. Compared to single objective problems, multiobjective problems are more difficult to solve, since there is no unique solution. There is a set of acceptable trade-off optimal solutions. This set is called Pareto front. The preferred solution, the one most desirable to the DM, is selected from the Pareto set. The Pareto set allows the decision maker to make an informed decision by observing a wide range of options since it contains the solutions that are optimum from an overall standpoint. A vector of decision variable is *Pareto Optimal* if there is no feasible vector of decision variables x which will decrease some criterion without causing a simultaneous increase in at least one another criterion. One of the most widely used methods for solving multiobjective optimization problems is to transform a multiobjective problem into a series of single objective problems. The weighted sum method is a traditional method that parametrically changes the weights among the objective functions to obtain the Pareto front. The weight of an objective can be chosen in proportion to the objective's relative importance in the problem. ε-constraint method, weighted metric methods, value function methods, goal programming methods are some of the other available methods [12]. For the power system studies, presented in this paper, the weighted sum method for multiobjective optimization is used.

Formulation for Power System Studies

For the power system studies presented in this paper, two goals (objectives) are considered for optimization, they 1.Economic Dispatch 2.Minimum Emission Levels of thermal generators of Electrical Power transmission system. In the multiobjective optimization, these two objectives are combined into a single objective function using the weighted sum method.

Economic Dispatch

The optimum power flow can be expressed as constrained optimization

Problem [ ] requiring the optimization of

$$\begin{aligned} & f=f(x,u) \\ & \text{Subject to} \\ & g(x,u)=0 \\ & h(x,u) \leq 0 \\ & u^{\min} \leq u \leq u^{\max} \\ & x^{\min} \leq x \leq x^{\max} \end{aligned} \tag{2}$$

In the above equations, f (x, u) is the scalar objective function, g(x, u) represents non- linear equality constraints (power flow equations), and h(x,u) is the non-linear inequality constraint of vector arguments x and u. The vector x consists of dependent variables (for example bus voltage magnitudes and phase angles). The vector u consists of control variable (for example, real power generation). Specifically, when the objective is to minimize the total fuel cost, the objective function can be expressed as the sum of the fuel cost for all the available generating units:

$$f_1(x,u) = \sum_{i=1}^{Ng} a_i + b_i P_{gi} + c_i P_{gi}^{\ 2} \tag{3}$$

where Ng is total number of generators

P_{gi} are the output of generators

a_i, b_i, c_i are the cost coefficients of the generators

Minimum Emission of Thermal units

The atmospheric emission can be represented by a function that links emissions with the power generated by every unit. Combined S_{O2} and $N_O x$ emission is a function of generator output and is expressed as follow.

$$f_2(x,u) = \sum_{i=1}^{Ng} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^{\ 2} + \chi_i \sin(\lambda_i P_{gi})) \tag{4}$$

Where $\alpha_i, \beta_i, \gamma_i, \chi_i, \lambda_i$ are emission coefficients of the generators

The combined optimization function with weighted objectives is

$$f\,(x,u)=\text{wt}^*\ f_1(x,u)+(1\text{-wt})^*\ f_2(x,u) \tag{5}$$

Where wt can assume any value in the range (1to 0).wt=1, the combined Optimization performs economic cost dispatch, wt=0, the combined optimization performs economic emission dispatch. For any other value of wt optimization is obtained for trade of solution (Pareto) between the objectives considered.

Big-Bang and Big-Crunch (BB-BC)

The BB–BC method developed by Erol and Eksin 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. Similar to other evolutionary algorithms, initial solutions are spread all over the search space in a uniform manner in the first Big Bang. Erol and Eksin associated the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a disorder or chaos state (new set of solution candidates).Randomness can be seen as equivalent to the energy dissipation in nature while convergence to a local or global optimum point can be viewed as gravitational attraction. Since energy dissipation creates disorder from ordered particles, we will use randomness as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos) .The proposed method is similar to the Genetic Algorithm in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang phase. In this phase, the candidate solutions are spread all over the search space in a uniform manner .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. Here, the term mass refers to the inverse of the merit function value. The point representing the centre of mass that is denoted by u_c is calculated according to:

$$u_c = \sum_{i=1}^{N} \tfrac{1}{f_i} u_i \Big/ \sum_{i=1}^{N} \tfrac{1}{f_i} \tag{6}$$

Where u_i is control variable in n-dimensional search space generated, *fi* is a fitness function value of u_i , *N* is the population size in Big Bang phase. After the Big

Crunch phase, the algorithm creates the new solutions to be used as the Big Bang of the next iteration step, by using the previous knowledge (centre of mass).This can be accomplished by spreading new off-springs around the centre of mass using a normal distribution (randn) operation in every direction, where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases:

$$u_{new} = u_c + (u_{lmt} * randn)/k \tag{7}$$

Where, u_{lmt} are the maximum and minimum limits of control variables.
randn is random normal number between -1 and 1.
k = (iteration number+1).

Application of BB-BC to power system studies

BB-BC is an unconstrained optimization function. In general, Optimization of power system with problem specific control variables $u(P_g$,E_g,taps,etc) has to satisfy equality g(x,u)(power flow equations), In-equality constraints $h(x,u) \leq h_{lmt}$ (Branch flow limits, generator reactive power limits, slack bus real power output), x(voltage magnitude and Phase angle of the load bus bars). In this paper, real power output of the Generator except slack bus real power output are control variables. Reactive power limits of the generator are handled in the power flow algorithm pv-pq bus type switching. Real power flows of the transmission branches and slack bus power i.e h(x, u) are satisfied by using penalty function method. There fore, the combined objective function gets transformed to unconstrained function ff as follows

$$f(x,u) + pen_b \sum_{b=1}^{n_b} \left(h_{lmt} - h(x,u)\right)^2 + pen_s \left(P_{Gslmt} - P_{Gs}\right)^2 \tag{8}$$

Where pen_b is penalty for branch real power flow violations.
Pen_s is penalty for slack real power generation.
Operational variables (x) for specified loads are calculated by Newton-Raphson (NR) Power flow algorithm.
The pseudo code of the BB-BC applied is given below

Step 1: Generate initial candidates in a random manner P_g's

Step 2: Solve NR Power flow and obtain voltage solutions, Calculate the fitness function (ff) values of all the candidate solutions.

Step 3: Find the centre of the mass p_{gc} using equation – 6.
Step 4: Calculate new candidates around the centre of the mass using equation -7. Bound the control variables within the limits, if control variables violate the limits.

Step 5: Until meeting a stopping criterion, return to step 2.

The above algorithm has to be repeated for all wt's (trade-off) of the DM.

Particle Swarm Optimization (PSO) is a heuristic search technique that simulates the movements of a flock of birds which aim to find food. The relative simplicity of PSO and the fact that it is a population-based technique have made it a natural candidate to be extended for multiobjective optimization. PSO optimization algorithm requires Optimization parameters constriction factor (cf) and inertia weight (w) to enhance the local and global search. In this paper, implementation of PSO and selection of tuning parameters for PSO are as explained in ref [7].

Discussion of Simulation Results

To test the BB-BC and PSO for multiobjective optimization as per the algorithms explained above, a MATLAB code is written, and is executed on Intel Pentium 1V, 2.8 GHz. Test cases considered for simulation are as follows.

Test case 1

IEEE-25bus system(Gangour),35 transmission lines,5 generators with generator 1 as slack generator line data, bus data, cost and NOx emission coefficients of the system is available [12].Total real power load 7.25 p.u and reactive power load is 2.23 p.u.

Test case 2

IEEE-30 bus standard test system, 41 transmission lines, with 6 generating units, two fixed shunts, and four transformers with generator 1 as slack generator. The bus and line data of this system is available [13], Cost coefficients and combined N_Ox, and S_{O2} coefficients are taken from [7]. Total real power load 2.8340 p.u and reactive power load is 1.2620 p.u.

Test case 1: Decision makers choice for trade-off vector is assumed as wt= [1, 0.8, 0.5. 0.2, 0]; In combined objective function of equation (5) considered wt=1, optimizes minimum cost dispatch, where as wt=0, optimizes for minimum emission dispatch. As The 'wt' departs from 1 tends towards 0, multiobjective function gives weightage towards minimum emission dispatch and picks those generators which increases the Cost of power generation and reduces the emission .BB-BC parameters are set to Maxiterations 100, population size 30.To compare with PSO, Maxiterations 100, population size 30.PSO also requires setting of Φ, cf and inertia weight w in equation (11). After few trails, cf=0.729, inertia weight w is set to 1.2 in the beginning of iteration process and gradually the value reduced to w/1.5 in successive iterations. Advantage of BB-BC, is that it does not require trails to select parameters for optimization. k in equation 7, is responsible for local search around Centre of mass of population as iteration number increases. k is taken as (iteration number+1). Fig(1),(2) indicates convergence characteristics for economic dispatch and emission dispatch by BB-BC and PSO.BB-BC converges in a stepped –manner without any oscillations. It is observed that to converge to an accuracy of 10^{-4} tolerance BB-BC needs 4-6 iterations more than PSO. However, both optimization methods nearly converge to average minimum in 10 to 30 iterations. Due to absence of Velocity terms for local and global searches in BB-BC for 100 iterations run take less time. Both optimizations are run for 100 independent times and the average execution times are computed which gives the average time for BB-BC 7.192732 s and for PSO 7.359188 s respectively.

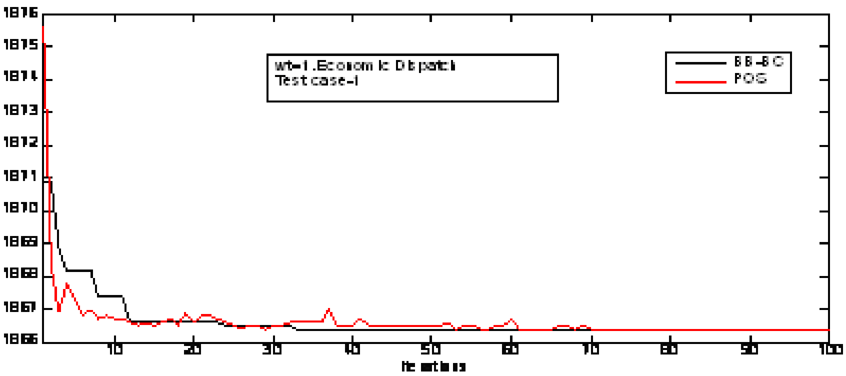

Figure 1: Convergence Characteristics wt=1, test case-1.

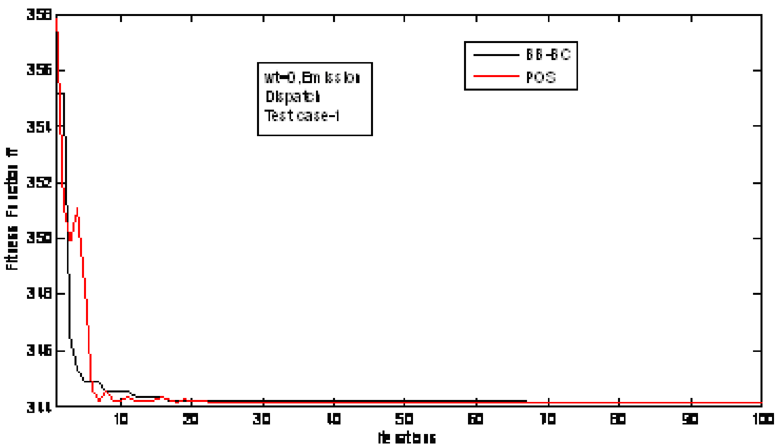

Figure 2: Convergence Characteristics wt=0, test case-1.

Table1, 2 shows trade-off (pareteo) solution and generator outputs (control variables of test case-1). Results are shown for a tolerance of 10^{-4} for cost and emission. For all trade off weights BB-BC solution is as superior as PSO for cost, emission dispatch and generator outputs.

Table 1: comparative trade-off solution of test case-1.

	BB-BC	POS	BB-BC	POS
Trade -off wt	Cost of generation $/hr	Cost of generation $/hr	Emission kg/hr	Emission kg/hr

1.0	1866.3881	1866.3868	575.2230	576.0738
0.8	1884.3083	1885.0337	380.4920	377.7807
0.5	1897.6055	1897.6713	348.6252	348.5591
0.3	1902.5054	1902.4991	345.1945	345.1971
0.0	1907.6596	1907.6268	344.1570	344.1569

Table 2: Comparative Generator outputs of test case-1

Trade-off weight(wt)		Pg(1) p.u	Pg(2) p.u	Pg(3) p. u	Pg(4) p.u	Pg(5) p.u	Real power loss (p.u)
1.0	BB-BC POS	2.99637 2.99991	1.096736 1.094519	1.105227 1.104519	0.509743 0.501048	1.669380 1.676733	0.1257 0.1267
0.8	BB-BC POS	2.161026 2.149600	1.036226 1.027528	1.714499 1.750000	0.679126 0.677772	1.820707 1.807582	0.1616 0.1625
0.5	BB-BC POS	1.816822 1.815337	1.090571 1.090609	1.750000 1.750000	0.750000 0.750000	2.037710 2.039369	0.1951 0.1953
0.3	BB-BC POS	1.710122 1.710188	1.119340 1.119810	1.750000 1.750000	0.750000 0.750000	2.131876 2.131332	0.2113 0.2113
0.0	BB-BC POS	1.610416 1.611085	1.149799 1.149037	1.750000 1.750000	0.750000 0.750000	2.217851 2.217823	0.2218 0.2279

Test case 2: Optimization parameters for this case are similar to test case-1. Emission function considered is combined S_{O2} and $N_{O}x$ and hence emission function has the same form as equation 4.For this case, Wt= [1, 0] are only weights that satisfies the trade-off (pareto) solution by both PSO and BB-BC. Fig 3, 4 shows the convergence characteristics of BB-BC and PSO respectively. For this case also both convergence characteristics, minimum dispatch results and generator outputs provided by BB-BC is as superior as to PSO. Table 3, 4 comparisons of results are shown. Times of executions are calculated similar to that in test case-1, for100 iteration average time of BB-BC is less than PSO. Average time for BB-BC 21.192732s and for PSO 22.259188 s respectively.

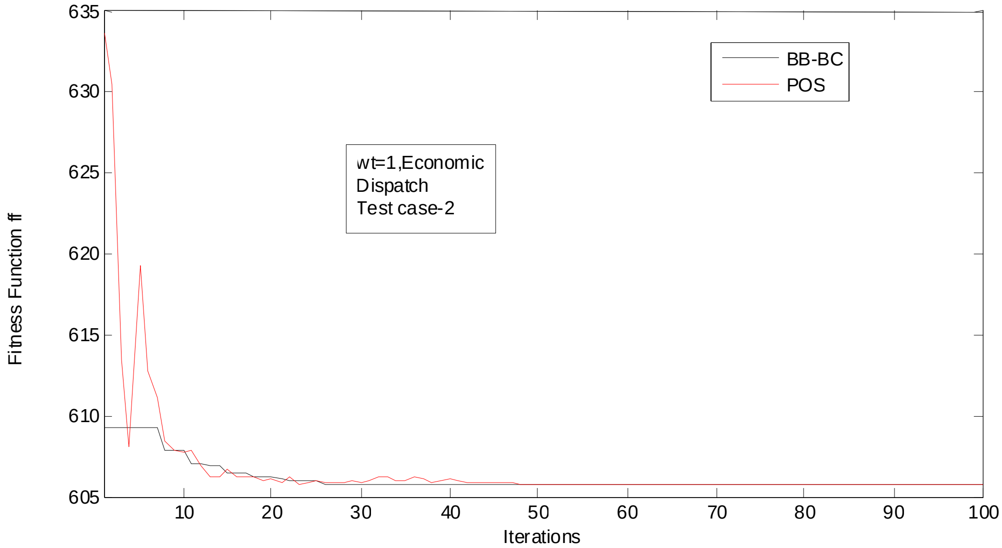

Figure 3: convergence Characteristics wt=1, test case – 2.

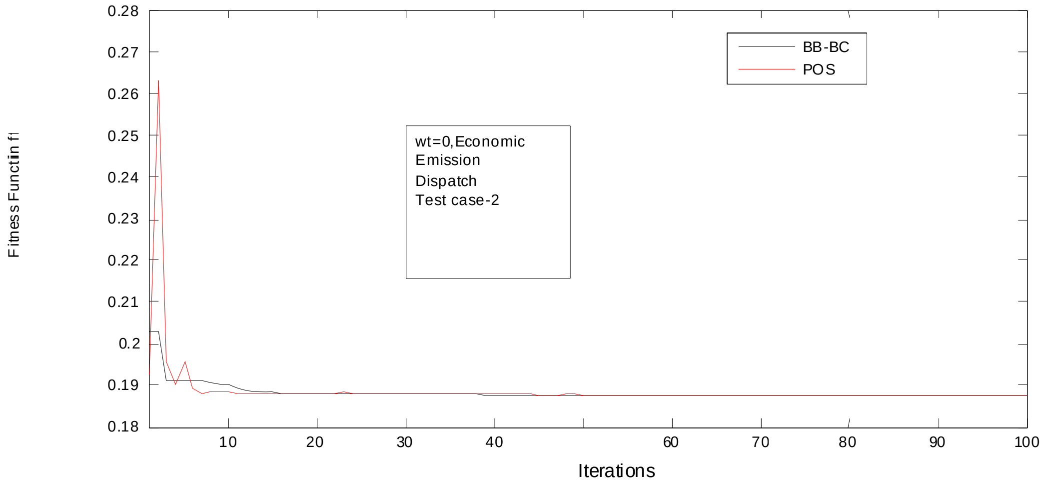

Figure 4: Convergence Characteristics wt=0, test case =2.

Table 3: comparative trade-off solution test case-2.

	BB-BC	POS	BB-BC	POS
Trade-off wt	cost of Generation $/hr	Cost of generation $/hr	Emission kg/hr	Emission kg/hr
1.0	605.7437	605.7457	0.2067	0.2067
0.0	640.0719	640.3200	0.1875	0.1875

Table 4: Comparative Generator outputs of test case-2.

Trade-off Weight(wt)		Pg(1) p.u	Pg(2) p.u	Pg(3) p.u	Pg(4) p.u	Pg(5) p.u	Pg(6) p.u
1.0	BB-BC POS	0.109255 0.108219	0.302857 0.301950	0.598409 0.596523	0.987130 0.985137	0.510126 0.518746	0.350301 0.347534 Real power loss(p.u) BB-BC 0.0241 POS 0.0241
0.0	BB-BC POS	0.392243 0.396126	0.496913 0.498989	0.504799 0.508535	0.450783 0.448739	0.510678 0.509479	0.505544 0.499002 Real power loss(p.u) BB-BC 0.1875 POS 0.1875

Conclusions

BB-BC optimization algorithm is applied for multiobjective optimization to obtain trade-off solutions for economic electrical real power cost dispatch and emission dispatch of thermal generating power transmission system using weighted sum method. BB-BC optimization is found to be solution effective and convergence is reliable .Most attractive feature is that like other EA, BB-BC does not require any trail parameters for optimization. A number of multiple solutions around centre of mass in first 10-15 iterations found to arrive at average minimum for all trade-off weights (wt) in both Test cases. The effectiveness of BB-BC has to be tested for optimal location of compensating devices, Reactive power optimization, congestion management etc with more number of control parameters with discrete step sizes for large scale Power transmission system.

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