Combined Economic and Emission Dispatch Using Big Bang–Big Crunch Optimization Algorithm

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***Abstract*-- This paper presents a new optimization method called Big Bang–Big Crunch (BB–BC) for solving the combined economic and emission dispatch (CEED). This problem has been addressed by considering economic and emission objectives separately or as a weighted sum of both objectives. The proposed method it is relies on the Big Bang and Big Crunch theory. It is one of the theories based on of the evolution of the universe problem. The results are obtained for various cost functions. The preference of the BB_BC is compared with other heuristic methods. The results show, clearly, that the proposed method gives better optimal solution as compared to the other methods.**

***Index Terms*-- Big Bang–Big Crunch, optimal power flow, combined economic and emission dispatch; CEED**.

I. Introduction

THE classical economic dispatch problem relies only on the minimization of the total fuel cost during the static operation of the electric power system. This single objective can no longer be considered alone due to the environmental concerns that arise from the gas emission produced by fossil fueled electric power plants. The clean air act amendments 'air facts' have been applied to reduce SO_2 (sulfur oxides) and NO_x (nitrogen oxides) emission from such power plants [1].

The electric power industry restructuration has created a highly vibrating and competitive market that altered many aspects of the industry [2]. A new operation philosophy has emerged to cope with these changes. Economic cost dispatch 'ECD' is one of the areas that was greatly impacted as a result of power industry deregulation. The main goal of 'ECD' is to allocate the optimal power outputs from different generating units at the lowest cost possible while meeting all system constraints. Emission dispatch 'ED'is similar to the ECD with the objective to be minimized is the gas emission instead of fuel cost. The two functions are conflicting in nature and they both have to be considered, simultaneously, to find overall optimal dispatch [3].

In the past decade, random search optimization methods, such as simulated annealing 'SA' [4], evolutionary programming 'EP' [5], genetic algorithms 'GA' [6]-[7], tabu search 'TS' algorithm [8]-[9] and particle swarm optimization 'SPO' 10], considered as probabilistic heuristic algorithms, have been successfully used to solve the dynamic ED problem.

A new optimization method relied on one of the theories of the evolution of the universe namely, the Big Bang and Big Crunch theory is introduced by Erol and Eksin [11] which has a low computational time and high convergence speed. According to this theory, the Big Bang phase energy dissipation produces disorder and randomness. It is considered as the main feature of this phase; whereas, 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 these points to a single representative point via a center 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, the Big Bang- Big Crunch optimization method has been employed to solve the problem of the combined economic and emission dispatch 'EED'. The feasibility of the proposed method is to demonstrate and compare it with those reported in the literature.

II. Problem Formulation

The EED problem is to minimize two competing objective functions, fuel cost and gas emission, while satisfying several equality and inequality constraints. Generally the problem is formulated as follows [12].

A. Economic Dispatch

The input / output fuel cost function of all generating units is typically modeled as a quadratic function. Thus, the total fuel cost F(PG) *[$/h]* can be expressed as [13]:

$$F(P_G) = \sum_{i=1}^{N} C_i(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \qquad (1)$$

Where

F: Total fuel cost in the system *[$/h]*.

a_i, b_i, c_i : Fuel cost coefficients of the i^{th} generating unit.
P_{Gi} : Power output of the i^{th} generator.
N : Number of thermal units.

B. Emission Dispatch

The solution of ED problem will give the amount of active power to be generated by different units at a minimum fuel cost for a given demand. But, the amount of gas emission is not considered in the pure ED problem. The amount of emission from a fossil based thermal generator unit depends on the amount of power generated by the unit. Total emission generated can also be approximated as a sum of a quadratic function of the active power output of the generators [14].

The minimum emission dispatch optimizes the above classical economic dispatch including.

$$E_{SO_2} = \sum_{i=1}^{n} (di_{SO_2} + ei_{SO_2} P_i + fi_{SO_2} P_i^2) \tag{2}$$

Where:
E_{SO2} : Total $SO2$ emission release [*Kg/h]*.
diSO2, *eiSO2* and *fiSO2 :* Emission coefficients for *SO2* of the i^{th} generating unit.

Similarly, the emission dispatch problem for NO_x can be defined as the following optimization problem,

$$E_{NOx} = \sum_{i=1}^{n} (gi_{NOx} + hi_{NOx} P_i + ki_{NOx} P_i^2) \tag{3}$$

Where :
ENOx: Total *NOx* emission release [*Kg/h]*.
giNOx, *hiNOx* and *kiNOx :* Emission coefficients for *NOx* of the i^{th} generating unit.

C. Problem constraints

The ultimate goal of the ED problem is to minimize the overall fuel cost function subject to the flowing constraints [13]:

- Generating capacity limits as inequality :

$$P_{Gi\min} \le P_{Gi} \le P_{Gi\max} \text{ for } i=1, ..., n \tag{4}$$

- Generation demand balance as an equality constraints:

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_L = 0 \tag{5}$$

- The system loss function is approximated by:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} (P_i B_{ij} P_j) \quad \text{MW} \tag{6}$$

Where
P_{Gimin} : Minimum power output limit of i_{th} generator.
P_{Gimax} : Maximum power output limit of i_{th} generator.
P_D: Demand power.
P_L: Power loss.
B_{ij} : Conductance's or loss coefficient elements.

D. Combined Economic and Emission Dispatch

The combined economic and emission dispatch problem 'CEED' is a contradictory problem: The role of the economic dispatch is to reduce the total fuel cost (operating cost) of the system at an increased rate of emissions. Where as, the emission dispatch reduces the total emission from the system by an increase in the system operating cost. The combined economic and emission dispatch problem seeks a balance between cost and emission problems [15].

The CEED problem can be formulated as,

$$Min\,[C(F, E_{SO_2}, E_{NOx})] \tag{7}$$

Where
F: Total fuel cost in the system,
E_{SO2} : Total SO_2 emission release [*Kg/h]*.
E_{NOx}: Total NO_2 emission release [*Kg/h]*.

The above mentioned multi- objective optimization problem can e converted to a single objective optimization problem by introducing price penalty factors as follows [16]:

$$Min\,[C = F + p_{fs}.E_{SO_2} + p_{fn}.E_{NOx})] \tag{8}$$

Where P_{fs} and P_{fn} are price penalty factors for SO_2 and NO_2 , respectively, blending the emission costs with the normal fuel costs. The total operating cost of the system due to the price penalty factors for SO_2 and NO_2 emissions is the cost of fuel plus the implied cost of emission. The procedure to find out the penalty factor p_f for NO_2 is as follows [17]:

- The fuel cost of each generator is evaluated at its maximum output:

$$F = \sum_{i=1}^{N} (a_i + b_i P_{i\max} + c_i P_{i\max}^2) \tag{9}$$

- The emission release of each generator for NO2 is evaluated at its maximum output,

$$E_{NOx} = \sum_{i=1}^{n} (gi_{NOx} + hi_{NOx} P_{i\max} + ki_{NOx} P_{i\max}^2) \tag{10}$$

- Pfn [i] for each generating unit is calculated

$$P_{fn}[i] = F(P_{i\max}) / E_{NOx}(P_{i\max}) \tag{11}$$

- Pfn[i] (i = 1, 2, 3, …, n) are arranged in ascending order.
- The maximum capacity of each unit, (Pimax) is added one at a time, starting from the smallest P_{fn}[i] unit until. $\sum P_{i\max} \ge D$
- At this stage Pfn[i] associated with the last unit in the process is the price penalty factor P_{fn} ($/Kg) for the given load demand D.

Similarly, the price penalty factor for SO_2 (P_{fs}) is calculated. Once the values of P_{fn} and P_{fs} are known, by minimizing the equation (8) subjected to the constraint equations (4) and (5), the optimal generation schedule can be obtained.

III. Big Bang–Big Crunch (BB–BC) Optimization Algorithm

The BB–BC method developed by Erol and Eksin [11] 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 [11] 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) [11].

The proposed method is similar to the GA 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 an uniform manner [11].

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 ''center of mass", since it is the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the merit function value [18]. The point representing the center of mass that is denoted by x_c is calculated according to:

$$\vec{x}^{c} = \frac{\sum_{i=1}^{N} \frac{1}{f^{i}} \vec{x}^{i}}{\sum_{i=1}^{N} \frac{1}{f^{i}}} \tag{12}$$

where x_i is a point within a generated n-dimensional search space generated, f_i is a fitness function value of this point, N 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 center 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 [11].

After the second explosion, the center of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met. The parameters to be supplied to normal random point generator are the center 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.

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 (center of mass). This can be accomplished by spreading new off-springs around the 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 [18]:

$$x^{new} = x^{c} + l.r/k \tag{13}$$

where x^c stands for 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 BB–BC approach takes the following steps [11]:

Step 1 - Form an initial generation of N candidates in a random manner. Respect the limits of the search space.

Step 2 - Calculate the fitness function values of all the candidate solutions.

Step 3 - Find the center of mass according to equation (12). Best individual fitness can be chosen as the center of mass.

Step 4 - Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse by using equation (13).

Step 5 - Return to Step 2 until stopping criteria has been met.

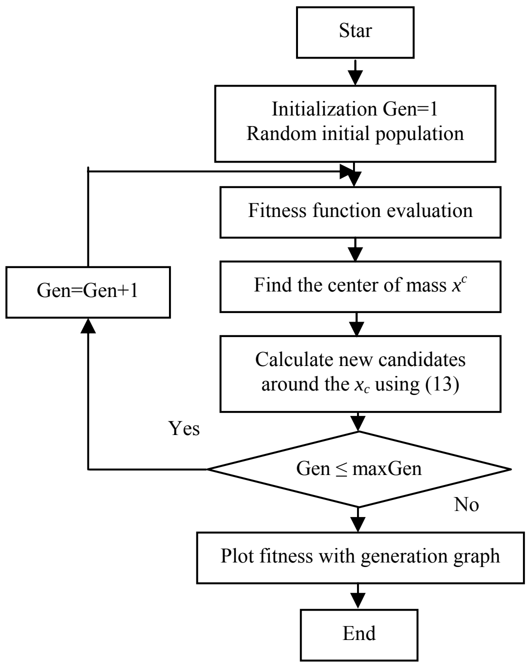

Fig. 1. BB–BC-OPF computational procedure.

IV. SIMULATION RESULTS AND DISCUSSION

The proposed BB－BC algorithm is tested on three generator test system whose data are given below [19].

The system demand is 850 [MW] in all simulations. The software was implemented by the MATLAB language, on a Pentium 4, 2.4 [GHz] personal microcomputer with 1 [GB] DDR RAM under Windows XP.

During the simulation, the following parameters in the BB－BC algorithms methods are used :

- The number of generation is 100 iterations and Size of population 50 individuals (candidates).
- The individual having minimum cost value is chosen for Big-Crunch phase.

- New population (Big Bang phase) is generated by using normal distribution principle with equation (13):

$$P_{Gi}^{k} = Pest_i + \left[(P_{GiMax} - P_{GiMin}).rand \right] / it \qquad (14)$$

Where k is the number of candidates, i is the number of parameters, $Pest_i$ is the value which falls with minimum cost, P_{GiMax} and P_{GiMin} are upper and lower limit parameters and it is the number of iterations.

TABLE I
FUEL COST COEFFICIENTS

Generator N°	a_i	b_i	c_i	P_{max} [p.u]	P_{min} [p.u]
1	100	200	10	0.50	0.02
2	120	150	10	0.60	0.03
3	40	180	20	1.00	0.05

The system transmission losses is calculated using a simplified loss expression:

$$P_L = 0.00003 P_{G1}^2 + 0.0000 P_{G2}^2 + 0.00012 P_{G3}^2 \text{ MW} \qquad (15)$$

SO_2 and NO_x emission coefficients are taken from reference [20] and are shown in tables 2 and 3, respectively..

TABLE II
SO2 EMISSION COEFFICIENTS

Generator N°	gi_{NOx}	hi_{NOx}	ki_{NOx}
1	0.5783298	0.00816466	1.6103e-6
2	0.3515338	0.00891174	2.1999e-6
3	0.0884504	0.00903782	5.4658e-6

TABLE III
SO2 EMISSION COEFFICIENTS

Generator N°	diSO2	eiSO2	fiSO2
1	0.04373254	-9.4868099e-5	1.4721848e-7
2	0.055821713	-9.7252878e-5	3.0207577e-7
3	0.027731524	-3.5373734e-4	1.9338531e-6

In this study, a developed algorithm has been applied for biobjective fuel cost , SO_2 emission dispatch and NO_x emission dispatch. The results for best fuel cost, best SO_2 emission and NO_x emission dispatch are summarized in tables IV to VI. Correspondingly, the convergence for optimized objective functions are shown in figures 2 to 4, respectively.

TABLE IV
SOLUTIONS OF MINIMUM FUEL COST

Evolutionary Algorithms	BB_BC	Tabu Search [20]	NSGA-II [19]
P1 [MW]	434.5152	435.69	436.366
P2 [MW]	300.7308	298.828	298.187
P3 [MW]	130.6044	131.28	131.228
Losses [MW]	15.8505	15.798	15.781
Fuel cost [$/h]	**8344.5952**	**8344.598**	**8344.606**
SO_2 Emission [Kg/h]	9.02261	9.02146	9.02083
NO_x Emission [Kg/h]	0.09871	0.09870	0.09866

TABLE V
SOLUTIONS OF MINIMUM SO2 EMISSION

Evolutionary Algorithms	BB_BC	Tabu Search [20]	NSGA-II [19]
P1 [MW]	552.7414	549.247	541.308
P2 [MW]	219. 0790	234.582	223.249
P3 [MW]	92.6958	81.893	99.919
Losses [MW]	14.5164	15.722	14.476
Fuel cost [$/h]	8397.023	8403.485	8387.518
SO_2 Emission [Kg/h]	**8.965936**	**8.874**	**8.96655**
NO_x Emission [Kg/h]	0.09684	0.09740	0.09637

TABLE VI
SOLUTIONS OF MINIMUM NOX EMISSION

Evolutionary Algorithms	BB_BC	Tabu Search [20]	NSGA-II [19]
P1 [MW]	508.291	502.914	505.810
P2 [MW]	250.600	254.294	252.951
P3 [MW]	105.854	108.592	106.023
Losses [MW]	14.747	15.8	14.784
Fuel cost [$/h]	8364.953	8371.143	8363.627
SO_2 Emission [Kg/h]	8.965936	8.874	8.96655
NO_x Emission [Kg/h]	**0.09592**	**0.0958**	**0.09593**

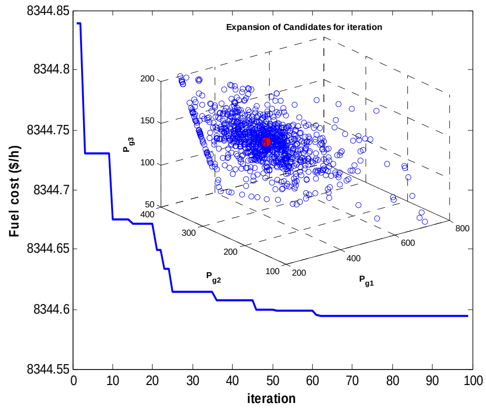

Fig. 2. Convergence characteristic of minimum fuel cost

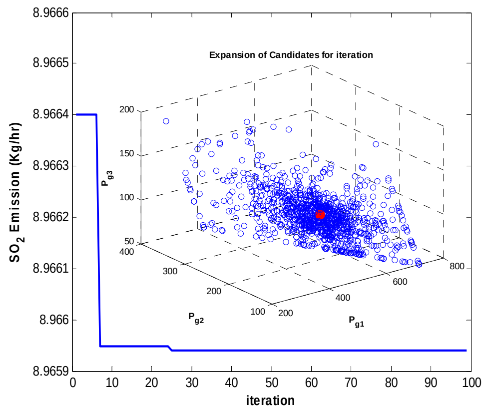

Fig. 3. Convergence characteristic of minimum SO2 Emission.

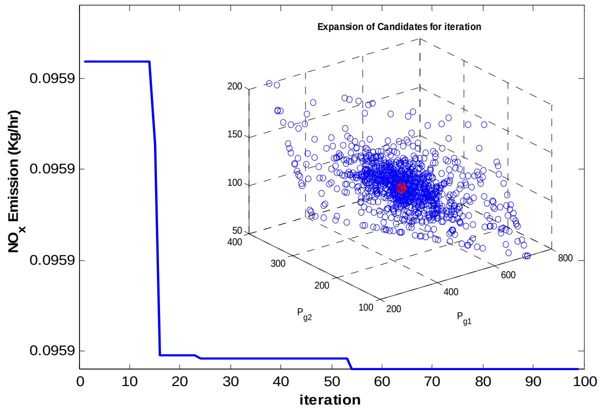

Fig. 4. Convergence characteristic of minimum NOx Emission.

The figures 2 to 4 show the minimum fuel cost, SO2 Emission and NOx Emission convergence of BB–BC algorithm for various numbers of generations. It was clearly shown that there is no great change in the fuel cost function value after 100 generations.

The best compromise solution selected using BB–BC algorithm is shown in table VII.

TABLE VII
BEST COMPROMISE SOLUTION

Evolutionary Algorithms	**BB_BC**
P1 [MW]	442.893
P2 [MW]	305.503
P3 [MW]	117.546
Losses [MW]	15.94
Fuel cost [$/h]	8345.813
SO_2 Emission [Kg/h]	9.01602
NO_x Emission [Kg/h]	0.09776
Cost total ($/h)	**25035.140**

The simulation results in the test system demonstrate the feasibility and effectiveness of the proposed method BB-BC in minimizing the operating cost of the generators. It is useful to compare the BB – BC technique to other methods such as Tabu Search [20] and NSGA-II [19] for obtaining and demonstrating high quality solution and validating our results.

I. CONCLUSION

The comparison of numerical results of combined economic and emission dispatch problem (CEED) using the BB‐ BC method with the results obtained by other heuristic approaches are performed to demonstrate the robustness of the present algorithm.

The BB-BC optimization has several advantages over other evolutionary methods. Most significantly, a numerically simple algorithm and heuristic methods with relatively few control parameters. Further, it presents the ability to solve problems that depend on large number of variables.

V. ACKNOWLEDGMENT

we would like to thank each member of the Editorial Board Members of the National Conference on Power Systems NCEN2010 for their Remarque's & Suggestions and participation in this paper.

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