



ISBN	978-81-929866-6-1
Website	icsscet.org
Received	25 – February – 2016
Article ID	ICSSCET022

VOL	02
eMail	icsscet@asdf.res.in
Accepted	10 - March – 2016
eAID	ICSSCET.2016.022

Big Bang – Big Crunch Method for Optimal Placement and Sizing of Distributed Generators for Power Loss Reduction and Voltage Profile Improvement

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Abstract- The Big Bang–Big Crunch method is a novel optimization method and this relies on one of the theories of the evolution of the universe; namely, the Big Bang and Big Crunch Theory. In the Big Bang phase, energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. Inspired by this theory, an optimization algorithm is constructed and it generates random points in the Big Bang phase and shrinks those points to a single representative point via a center of mass or minimal cost approach in the Big Crunch phase. The Distributed Generators (DG) placement and size in radial distribution systems using Big Bang - Big Crunch (BB-BC) Algorithm is exhibits voltage profile improvement and reduction in losses. The results showed that introduced method is superior to simple GA in terms of solution quality and number of iterations.

I. INTRODUCTION

In recent years, the penetration of distributed generator (DG) into distribution systems has been increasing rapidly in many parts of the world. The main reasons for the increase in penetration are the liberalization of electricity markets, constraints on building new transmission and distribution lines, and environmental concerns [1]–[3]. Technological Advances in small generators, power electronics, and energy storage devices for transient backup have also accelerated the penetration of DG into electric power generation plants [4]. At present, there are several technologies used for DG applications that range from traditional to non-traditional technologies.

The former is non renewable technologies such as internal combustion engines, combined cycles, combustion turbines, and micro turbines. The latter is renewable technologies such as solar, photovoltaic, wind, geothermal, ocean, and fuel cell. The main advantages of using renewable-energy-based DG sources are the elimination of harmful emissions and inexhaustible resources of the primary energy. However, the main disadvantages are relative low efficiency, high costs, and intermittency [5], [6]. As the penetration of DG units increases in the distribution system, it is in the best interest of all players involved to allocate them in an optimal way such that it will increase reliability, reduce system losses, and hence improve the voltage profile while serving the primary goal of energy injection. DG units are modelled as synchronous generators for small hydro, geothermal, and combined cycles; combustion turbines; and wind turbines with power electronics. Induction generators are used in wind and small hydropower generation. DG units are considered as power electronics inverter generators or static generators for technologies such as photovoltaic (PV) plants and fuel cells [7], [8]. For instance, DG using a PV grid-connected converter is controlled on the basis of the droop-control technique presented in [9]–[17]. The converter is capable of providing active power to local loads and injecting reactive power to stabilize load voltages. Furthermore, the type of DG technology adopted will have a significant bearing on the solution approach. For example, in [18], the installation of synchronous machine-based DG units that are close to the loads can lead to a gain in the system voltage stability margin; on the other hand, in the case with an induction generator, the system stability margin is reduced. Given the choice, DG units should be placed in

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Cite this article as: M Sudheer Chandra, Y LakshmiReddy, Sathiya narayanan T, Dr M Sydulu. "Big Bang – Big Crunch Method for Optimal Placement and Sizing of Distributed Generators for Power Loss Reduction and Voltage Profile Improvement". *International Conference on Systems, Science, Control, Communication, Engineering and Technology 2016*: 109-113. Print.

appropriate locations with suitable sizes and types to enjoy system-wide benefit. However, in this approach, the optimal sizing is not considered. The genetic algorithm (GA)-based method has been presented to determine the size and location of DG [19], [20]. GA is suitable for multi objective problems and can lead to a near optimal solution but demand higher computational time. An analytical approach based on an exact loss formula has been presented to find the optimal size and location of single DG [21]. In this method, a new methodology has been proposed to quickly calculate approximate losses for identifying the best location; the load flow is required to be performed only twice. In the first time, it is applied to calculate the loss of the base case, and in the second time, it is used to find the minimum total loss after DG placement. Although this method requires less computation, single DG capable of delivering real power only is considered. A probabilistic-based planning technique has been proposed for determining the optimal fuel mix of different types of renewable DG units (i.e., wind, solar, and biomass) in order to minimize the annual energy losses in the distribution system [22]; however, DG units capable of delivering real power only is considered in this paper and the Proposed method tested on IEEE 33 and IEEE 69 bus distribution systems with single DG and two DGs.

The remainder of this paper is organized as follows: Section II explains the Problem formulation; Section III explains the proposed Big Bang–Big Crunch method. Procedure for DG placement and sizing using Big Bang–Big Crunch method is in Section IV. The test distribution systems and simulation results in Section V. Finally, the major contributions and conclusions are summarized in Section VI.

II. Problem Formulation

A. Power Loss Reduction

Normally, shunt capacitors and DGs are employed to aid in reducing power loss in distribution system. However, the latter is a better option in terms of feeder systems compensation. From a line current perspective, shunt capacitor reduces a portion of the reactive line current only. However, DG reduces portions of both active and reactive line currents. Thus, the latter decision is superior under optimal solution achievements.

B. Real Power Loss and Bus Voltage

The real power loss in n-bus system is given by [1].

$$\sum_{i=1}^n \sum_{j=1}^n \frac{Z_{ij}}{V_i V_j} [\cos(\delta_i - \delta_j)(P_i P_j + Q_i Q_j) + \sin(\delta_i - \delta_j)(Q_i P_j + P_i Q_j)] \quad (1)$$

For n connected lines to j-bus, the bus voltage can be determined by,

$$V_j = \sum_{j \neq i}^n 0.5 [V_i + Z_{ij}] \sqrt{\frac{V_i^2}{Z_{ij}} - \frac{S_{load}}{0.25 Z_{ij}}} \quad (2)$$

Where V_j is affected by the total power load, S_{load} connected directly to j-bus.

III. Big Bang – Big Crunch Algorithm

Big Bang Phase: 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, randomness can be used as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos). 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.

Big Crunch phase: 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 can be named as the center of mass, since the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the fitness function value. The point representing the center of mass that is denoted by x_c is calculated according to the formula

$$x_c = \frac{\sum_{i=1}^n \frac{1}{f_i} x_i}{\sum_{i=1}^n \frac{1}{f_i}} \quad (3)$$

Where x_i is a point within an 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 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 members to be used as the Big Bang of the next iteration step. This can be done in various ways, the simplest one being jumping to the first step and creating an initial population. The algorithm will have no difference than random search method by so doing since latter iterations will not use the knowledge gained from the previous ones; hence, the convergence of such an algorithm will most probably be very low. An optimization algorithm must converge to an optimal point; but, at the same time, in order to be classified as a global algorithm, it must contain certain different points within its search population with a decreasing probability. To be more precise, we mean that, large amount of solutions generated by the algorithm must be around the so-called optimal point but the remaining few points in the population bed must be spread across the search space after certain number of steps. This ratio of solution points around the optimum value to points away from optimum value must decrease as the number of iterations increases; but, in no case, it could be equal to zero, which means the end of the search. This convergence or the use of the previous knowledge (centre of mass) can be accomplished by spreading new off-springs around this centre 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.

After the second explosion, the centre of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met. The two 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. The accumulation around the centre of mass can be observed, but there still exist a few points out of the ensemble.

The deviation term will reach zero as iterations go to infinity, thus we can conclude there will always be off-springs which will be located far from the centre of mass with decreasing probability but never equal to zero bearing the potential to affect the so found centre of mass towards itself if it has higher fitness value than the remaining members. This is the key property that assures the global convergence of the algorithm [23].

IV. DG Placement and Sizing Using BB-BC Algorithm

A. Summarizing the Steps Involved in BB-BC Algorithm

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 (1). Best fit Individual can be chosen as the centre of mass instead of using Equation (3)

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. This can be formalized as:

$$X_{new} = X_c + (l_r / k) \quad (4)$$

where X_c stands for centre 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.

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

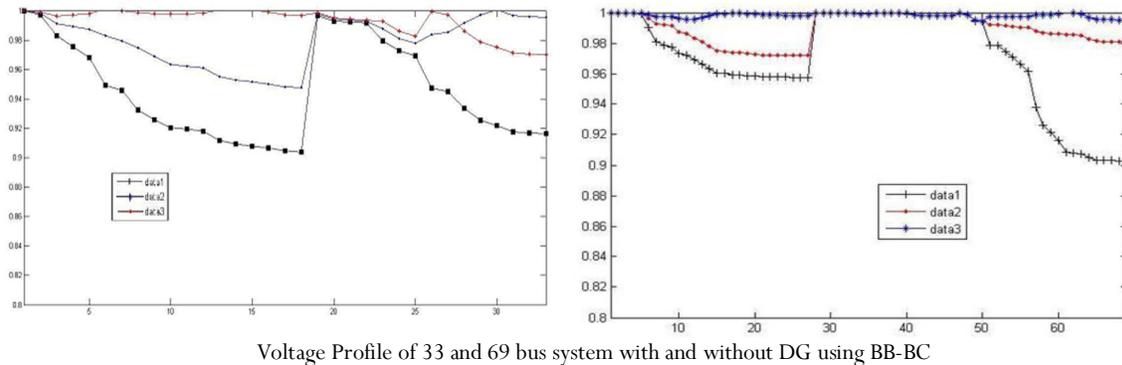
Implementation of BB-BC for Optimal Single DG Placement

1. Initialize the population size and limits of distributed generator.
2. Initialize the population within the limits randomly (Big Bang Phase). % data has three variables, location, Pdg size and Qdg size respectively.
3. Initialize the iteration count as $iter = 1$.
4. Apply DG for corresponding buses.
5. Run Load flow and evaluate power loss and fitness function.
6. Calculate the Centre of mass using equation (3) and new candidates around the centre of mass are calculated using equation (4)

$$X_{new} = X_c + (l_r / k)$$
 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.
7. Check stopping criterion i.e., $P_{total}(end, 1) - P_{total}(1, 1) < 0.001$, stop the iteration. Print location of DG and size. Also print the power losses, Voltage Magnitude and phase angles. Else increase iteration counter and go to step 4.
8. End of the Algorithm.

V. Simulation Results

The proposed solution methodology has been implemented in MATLAB version 2009b and tested on standard IEEE 33 and IEEE 69 bus test systems. The voltage profile for IEEE 33 bus and IEEE 69 bus systems after DG placement as shown fig 1 and fig2.



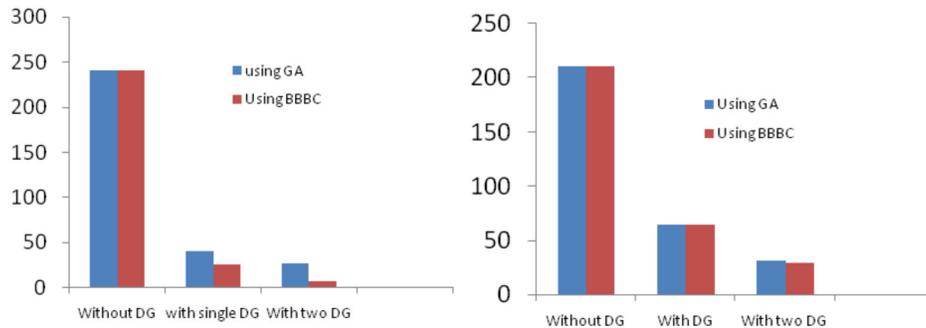
****In figures

Data1 corresponds to voltage without DG

Data2 corresponds to voltage with Single DG

Data 3 corresponds to voltage with two DG

The proposed method results are compare with GA technique is as shown in below fig 3 and fig 4.



Comparison of losses for 33 and 69 bus system

Table I. Results for 33 BUS And 69 bus systems

For 33 Bus System	Without DG	With Single DG	With two DG	For 69 Bus System	Without DG	With Single DG	With two DG
GA	210.8433	64.5303	30.9919	GA	242.1593	40.937	27.6148
BB-BC	210.8433	64.2945	28.6249	BB-BC	242.1493	26.045	7.1018

VI. Conclusion

In this paper, the novel optimization method i.e., relies on one of the theories of the evolution of the universe named Big Bang–Big Crunch method is proposed to minimize the power loss and improve the voltage profile in the system by an efficient load flow method. For the IEEE-33 bus system GA converges quickly giving satisfactory results while BB-BC though takes the least number of iterations for convergence and the best reduction in active power loss. For the IEEE-69 bus system GA converges ahead of others and takes more number of iterations. BB-BC takes less number of iterations for convergence. The algorithm gives the optimum solution for placement and sizing of DGs with a few number of load flow iterations. Therefore, the proposed method can be effectively used in real time applications when large distribution systems under widely loaded conditions are concerned.

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