Big Bang Big Crunch Optimization for Determination of Worst Case Loading Margin

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Abstract –

While increasing the system load in a predefined manner we can determine the worst case loading margin, also concerned about the loading pattern that leads to smallest stability margin. CSNBP (closest saddle-node bifurcation point) can be calculated using Big Bang Big Crunch optimization even if the transfer limit is not smooth. CSNBP is formulated as an optimization problem and is applied on a simple radial system and also on IEEE 14 bus system in the presented paper.

Keywords- Big Bang-Big Crunch, loading margin, voltage collapse, Saddle node bifurcation point, distance to instability

1. INTRODUCTION

There are two important aspects of the power system, whose study is must for every power system engineer which are voltage stability and voltage collapse. Voltage stability is the ability of the power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbances [1].The inability of the power system to meet the demand for reactive power tending the system towards instability. Its consequences may have widespread impact. Also voltage collapse is the process by which the sequence of events accompanying voltage instability leads to a low unacceptable voltage profile in a significant part of the power system [1].

For the non linear systems, while increasing the load in the steps until the system become unstable, we can calculate voltage instability for which power system fails to converge by using the concept of bifurcation. The word "bifurcation'' actually comes from the concept of different branches of equilibrium point intersecting each other. Bifurcation occurs at any point in parameter space, for which qualitative structure of the system change for the small variation of the parameter vector. To understand the bifurcation more easily, we can say that the change in anything which is given below constitutes the bifurcation:

1. Number of equilibrium points;
2. Stability of equilibrium points or limit cycles;
3. Number of limit cycles;
4. Period of periodic solutions;

There are two methods to calculate local bifurcation, i.e., direct method and indirect (continuation) method [14]. In direct method non linear algebraic equation is solved using any iterative methods like Newton-Raphson method. but the obtained convergent solution is just one point on multi-parameter boundary. Thus lacks global information of multi-parameter local bifurcation boundary. Another is Indirect method also known as continuation method. Firstly this method tracks the equilibrium curve of the power system point by point as the parameter vary, and by interpolation method it locates the possible local bifurcation based on critical eigenvalues of the related system Jacobian matrix.

A SNB is a point where the two branches of equilibria meets. At bifurcation the equilibrium becomes a saddle node thus known as Saddle Node Bifurcation(or SNB). The necessary condition is that the state Jacobian has to be singular. By determining the determinant or the smallest eigen value of the system Jacobian, we can find out the closeness of the system to voltage collapse point or saddle node bifurcation point.

These methods recognize and predict proximity to the bifurcation point in power systems. In general, bifurcation detection algorithms have two steps. In the first step, the system load is increased and the load flow calculation is confirmed. In the second step, eigenvalues of the state matrix are calculated and finally stability of the system is checked. If the system is stable, the load should be increased and if the system is unstable, the load should be decreased and the algorithm should be continued until the vicinity of the system to instability is less than a certain value. For computing a closet SNB and worst case load power margin for voltage collapse. The Big-Bang method determines the worst loading direction considering SNB. This iterative method of power flow has been presented to estimate maximum loading conditions.

When the bifurcation parameter approaches the bifurcation value, the system equilibrium approaches a singular surface in state space. This singular surface causes a change in dynamic structure change. The property of singularity induced bifurcation is that the eigenvalues of the differential equation model bifurcate virtually simultaneously with the bifurcation of the load flow. An iterative method can be used to compute the load powers at which bifurcation occurs and are locally closest to the current operating load powers. The model used determines the voltage collapse point as saddle node bifurcation point (SNB). At this point the eigenvalue is either nearly or equal to zero. The study of static voltage stability gives the important concept of transfer limit surface [4]. The transfer limit surface is defined as the hypersurface in the load parameter surface. Also we can say that it is the upper limit imposed by the system characteristics on the power flowing from generator buses to load buses[6]. In static voltage assessment the transfer limit surface is known as singular surface and is denoted by S having active and reactive component of load as coordinate. It divides the load parameter into two region.

Hypresurface represents the locus of all coordinates of P and Q which results in a zero eigenvalue of jacobian [2]. The points which are existing below the transfer limit surface represent the voltage stable condition and the points which are
above the transfer limit surface ‘‘S’’ represents voltage unstable condition. On gradual increasing of load, if the operating point reaches to transfer limit then it results into voltage collapse. When the constraints are not considered the hypersurface/ transfer limit surface is not smooth but we have to take care of the smoothness of the transfer limit surface. Normal vector approach will find a local minimum in the condition when the reactive power limits are considered in such case the transfer limit surface may not smooth [9-10]. A boundary between the regions corresponds to maximum load the network can supply. The maximum transfer of active power, i.e., the usual static stability limit, is a special case of maximum transfer of active/reactive power. It is the tip of the “nose” of the Q-V curve [14].

To operate the system with an adequate security margin, we have to estimate the loading margin (LM). LM is defined as the distance between the current operating point and voltage collapse point [2]. There are a lot of approaches by which we can find out the maximum loading point of the system. The problem can be formed as an optimization problem and can be solved using any optimization technique [7-10]. The PV curve is a power voltage relationship. Figure 1 is an illustration of a typical PV diagram. ‘’V’’ in the vertical axis represents the voltage at a particular bus while ‘’P’’ in the horizontal axis denotes the real power at the corresponding bus or an area of our interest. The solid horizontal nose-shaped curve is the network PV curve while the dotted parabolic curve is the load PV curve.

In this paper the closest saddle-node bifurcation point (CSNBP) is formulated as an optimization problem and solved using Big Bang Big Crunch Algorithm. In most of the existing method the attention has been focused on obtaining SNBP with specific direction of load increase. There are lots of optimization methods to calculate this, like PSO [6], Genetic Algorithm etc. we can also use iterative method to compute the shortest distance to instability.

2. STATIC VOLTAGE STABILITY AND SURVEYING POSSIBLE CONTINGENCIES

Power flow solutions near the critical point are prone to divergence and no solution being obtained. For this reason, CPF method is used to overcome this stability problem. The loadability of a bus in the power system depends on the reactive power support that the bus can receive from the system. As the system load approaches the maximum loading point, both real and reactive power losses increases rapidly. A common assessment of system stability is expressed by the load margin to the point at which the voltage collapses. The power flow equation for the power system has the following form:

$$f(x, \lambda) = 0 \qquad (1)$$

where

$$x = \begin{bmatrix} V \\ \theta \end{bmatrix} \text{ and } \lambda = \begin{bmatrix} P \\ Q \end{bmatrix}$$

where x is a state vector of power flow problem and typically represents V and θ, i.e., the bus voltages and angles and can also be used to compute other system variables like generator reactive power injections Q. The variable λ represents a scalar parameter or loading factor used to simulate the load changes that drive the system to the collapse point. Assume current operating load power λ_0 at which the corresponding equilibrium x_0 is stable. As the load parameter λ vary from the current load powers λ_0, the equilibrium x will vary in the state space. If the parameter vector λ and the corresponding system state vector x are such that the power flow jacobian matrix j_x is singular then the system reaches to its voltage stability critical point.

The system may be operating at a stable equilibrium point but a contingency at maximum loading point may land unstable region or where there is no solution to the system equations. The main reason for low voltage profile for some contingency and therefore smaller MWM is the insufficient reactive power in the vicinity of the low voltage buses [11]-[13].Let S is transfer limit surface in N dimensional parameter space such that $j_x (x_* ,\lambda_*)$ is singular and λ_* is a point on S. At critical load powers x_1 the system can lose stability by x disappearing in a saddle node bifurcation and we denote the set of such x_1 in the load power parameter space by S.

The saddle node bifurcation instability when the load powers encounter C can cause catastrophic collapse of the system voltages and blackout. S typically consists of hypersurfaces and their intersections. The instability can be avoided by monitoring the position of the current load powers λ_0 relative to S and taking corrective action if λ_0

moves too close to S**.** In particular it is useful to calculate a critical load power λ**,** in S for which| λ_* , λ_0| is a local minimum of the distance from λ_0 to S. Then the line segment $\lambda_0 - \lambda_*$**,** represents a worst case load power parameter variation and also measures the proximity to saddle node bifurcation. That is, the worst case load power margin $|\lambda_0 - \lambda_*|$ is a voltage collapse index. We call the bifurcation at **A,** 'a closest saddle node bifurcation' with the understanding that the distance to bifurcation is measured in parameter space relative to the fixed value λ_0**.** The worst case load power margin is a voltage collapse index called CSNBP. From a practical point of view, the closest bifurcation point in a direction of reasonable load increase is most important.

2. PROBLEM FORMULATION

The CSNBP is formulated as an optimization problem. For a given initial point (x_0,λ_0) , λ can be increased along different directions. Loading Margin (LM) depends upon on the direction along with λ is increased. Our aim is to find the direction of the parameter vector which gives minimum LM. Thus the objective can be written as

$$\min \quad LM = \sqrt{\left(\sum_{i=1}^{n} \Delta Pi\right)^2 + \left(\sum_{i=1}^{n} \Delta Qi\right)^2} \qquad (2)$$

where

ΔPi =Change in active power load at bus i from initial operating point to voltage collapse point.

ΔQi =Change in reactive power load at bus i from initial operating point to voltage collapse point.

n = total number of load buses.

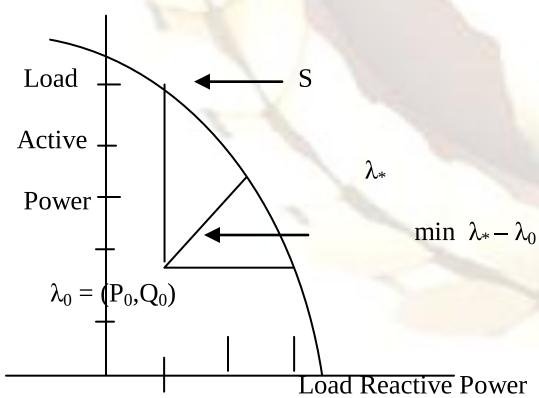

Fig. 1 **PV Curve contains hypersurface 'S'**

The Big Bang Big Crunch algorithm is applied to determine the shortest distance to worst case loading margin. To understand the Big Bang Big Crunch algorithm, a brief description is given below.

3. BRIEF DESCRIPTION OF BIG BANG BIG CRUNCH (BBBC) METHOD AND IT'S IMPLEMENTATION

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 [3] which has a low computational time and high convergence speed. It 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.

According to this 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. 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. 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 use of Big Bang Big Crunch algorithm involves the following steps:

i] Creation of initial population

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.

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.

ii] Fitness function

The fitness function is defined here as

$$F = \begin{cases} LM & \lambda \epsilon S \\ B & \lambda \epsilon S \end{cases} \qquad (3)$$

Where
LM = Loading Margin given by (2)
B = a large positive constant

The condition $\lambda \epsilon S$ is checked by computing the eigenvalue of the full jacobian matrix of the system. We can say that the parameter vector λ belongs to the hypersurface S, if the eigenvalue is closed to zero. Hence the given fitness function given above is minimized by applying Big Bang Big Crunch Method.

iii] The Big Crunch phase and Center of mass

The Big Bang should be followed by a Big Crunch. Hence we start analyzing the population generated in Big Bang for Big Crunch phase. As mentioned before, the Big Crunch phase has a single point where all mass is a concentrated. So for a given Big Bang configuration to obtain a Big Crunch, we need to calculate a point where all the mass can be placed safely. This point is called as center of mass which is defined as a point where the entire mass of system is said to be concentrate [5].
The point representing the center of mass that is denoted by $\vec{x}^c$ is calculated according to:

$$\vec{x}^c = \frac{\sum_{i=1}^{N} \frac{\vec{x_i}}{f_i}}{\sum_{i=1}^{N} \frac{1}{f_i}} \qquad (4)$$

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 center of gravity.

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.

$$X_{new} = X_c + l.r/k \qquad (5)$$

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.

iv] Termination criteria

Like GA, BBBC is terminated after specified maximum number of iteration. There is also another termination strategy which involves population convergence criteria. But in this work BBBC is terminated after specified maximum number of iterations.

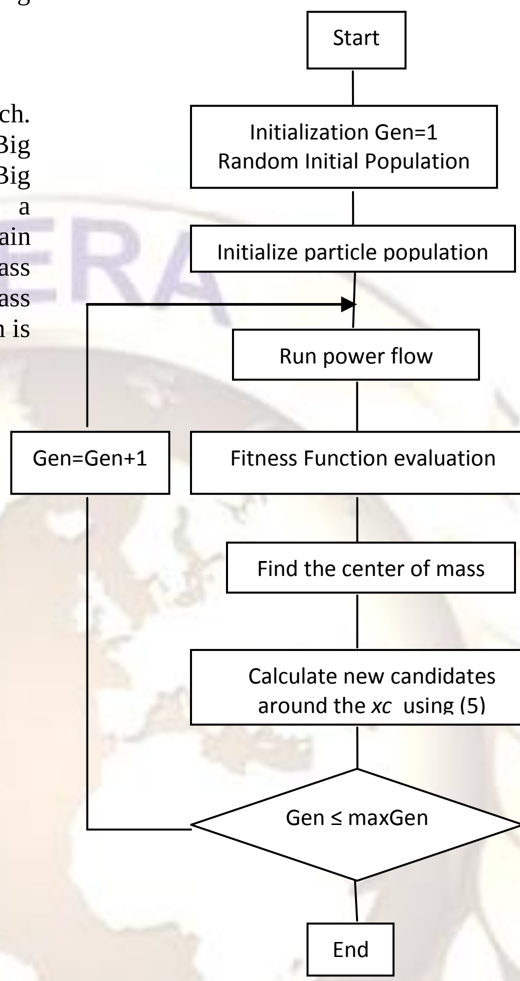

Fig. 2. Flow chart of Big Bang Big Crunch Algorithm

v] BBBC implementation for determining CSNBP

The BB–BC approach takes the following steps:

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 (Eq. no. 4).

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 of using(5).

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

For any system for finding the minimum distance from an initial load level P_0, Q_0 to S is as follows:

1. Increase load from P_0, Q_0 in some direction until eigen value of the jacobian is practically zero. The load level P_1, Q_1 correspond to this point is the stability limit. This point P_1, Q_1 lies on, or is extremely near, S.
2. For the condition at P_1, Q_1, perform modal analysis and determine the left eigenvector of the full jacobian matrix. The left eigenvector cantains elements which provide the increment of MW and MVAr load for each bus. The eigenvector points in the shortest direction to singularity, which is there fore normal to S.
3. Go back to the base case load level P_0, Q_0 and load the system again, but this time in the direction given by the left eigenvector found in 2.
4. Again we return to the base case P_0, Q_0 and load the system in the direction of the new eigenvector given in 3. This process is repeated until the computed eigenvector does not change with each new iteration. The process will then have converged.

5. SIMULATION AND RESULT

The ability of the proposed method has been tested on simple radial system and IEEE 14 Bus system. And the results obtained for simple radial system are given in table no. 1 and the results obtained for IEEE 14 bus system is given in table no. 2 are the application result for proposed method.

Example 1. Simple radial 2 bus system

A simple radial system is given in fig. 3. In this we assume that P and Q vary independently. So we can say that in the given problem the number of variable is 2. We have applied the Big Bang Big Crunch algorithm on this current operating step to determine the shortest distance to voltage collapse. The initial system operating condition is given in the table below. For the sake of the results the results of the iterative method and GA is shown in the table below.

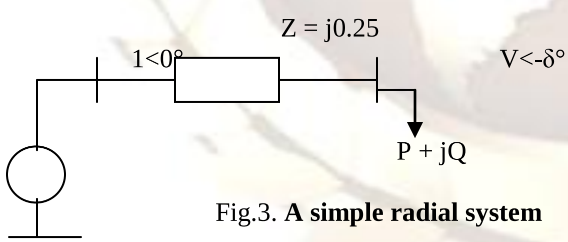

Fig.3. **A simple radial system**

Table 1: For simple radial system Value of real and reactive power load at voltage collapse point

Method	Initial operating point λ_0 (p.u.)		Voltage collapse point λ^* (p.u.)		Distance to instability (MVA)	Left Eigen-vector η_i	Min Eigen Value
	P_0	Q_0	P_*	Q_*			
Iterative Method	*0.8*	*0.4*	*0.9576*	*0.7717*	*40.37*	*[0.4378 0.8991]^T*	*0.0829*
GA Method	*0.8*	*0.4*	*0.9729*	*0.7633*	*40.23*	*[0.4559 0.8296]^T*	*4.9715× 10^{-3}*
Proposed Big Bang Big Crunch	*0.8*	*0.4*	*1.0429*	*0.7107*	*39.44*	*[0.4627 0.8273]^T*	*3.919 ×10^{-3}*

Example 2. IEEE 14 bus system

The IEEE 14 bus system consisting of three synchronous condensers and three synchronous machines, in which at bus 3, 6, and 8 synchronous condensers are connected only to supply reactive power in the system. There are 2 generators located at bus no.1 and bus no.2. There are 14 buses and 20 branches and supplying 11 loads total of 259 MW and 77.4 MVAR at base case. Initial operating point is assumed as base case loading point.

To obtain the minimum loading margin, it is assumed that active and reactive power of load bus can vary independently. There are 22 variables in the system because there are 11 load buses. The obtained results are given in the table no. 2.

We keep the power factor constant while obtaining the curve of all load, we gradually increase the base case. The method is being used here to calculate the CSNBP. Voltage collapse occurs at loading margin of 0.6263. i.e., 62.63% increase in load at all buses keeping power factor constant.

Bus No.	Initial operating point λ_0 (p.u.)		Voltage collapse point λ^* (p.u.)	
	P_0	Q_0	P_*	Q_*
2	*0.217*	*0.127*	*0.2180*	*0.1270*
3	*0.942*	*0.190*	*0.9443*	*0.1900*
4	*0.478*	*0.000*	*0.4785*	*0.0001*
5	*0.076*	*0.016*	*0.076*	*0.0159*
6	*0.0112*	*0.075*	*0.128*	*0.0749*
9	*0.295*	*0.166*	*0.2954*	*0.1660*
10	*0.090*	*0.058*	*0.0908*	*0.0580*
11	*0.035*	*0.018*	*0.0358*	*0.0179*
12	*0.061*	*0.016*	*0.0650*	*0.0160*
13	*0.0135*	*0.058*	*0.01354*	*0.0580*
14	*0.149*	*0.050*	*0.1495*	*0.6692*
Total Load	*2.59*	*0.774*	*2.49484*	*1.393*

Table 2: For IEEE 14 Bus System
For IEEE 14 bus system initial operating point and load at various buses is given which cause voltage collapse

All the reactive power sources in IEEE 14 bus system are located from bus number 1 to 8. But from bus number 9 to bus number 14 there is no reactive power support available. Therefore the voltage becomes unstable due to increase in load in the weak area.

5. CONCLUSION

The BBBC method is applied to solve the CSNBP problem. This worst case loading margin to voltage collapse point problem is formulated as an optimization problem and solved using BBBC. In this paper, a new advancement, using Big Bang Big Crunch (BBBC) algorithm is successfully depicted for CSNBP problem with dynamic constraints. The suggested approach is found to be more stable than the conventional methods and computationally superior. And it proves us a promising tool for minimum loading margin evaluation.

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