Big-Bang and Big-Crunch (BB-BC) and FireFly Optimization (FFO): Application and Comparison to Optimal Power flow with Continuous and Discrete Control Variables

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Abstract: Big-Bang and Big-crunch (BB-BC), a heuristic optimization method is based on the concept of universal evolution. FireFly optimization (FFO), also a recent heuristic optimization method, is based on the concept of flashing behaviour of lightingbugs. Both the optimization methods are applied to obtain the solution of the Optimal Power Flow (OPF) with continuous and discrete control variables for quadratic generator output cost functions. The continuous control variables are generating unit active power outputs and generator bus voltage magnitudes, while the discrete ones are transformer-tap settings and switchable shunt devices. A number of functional constraints such as load bus voltage magnitudes, line flows and reactive power capabilities are included as quadratic penalties in the optimization function. A comparative simulation results for Ward –Hale 6 bus system with seven control variables and IEEE 30 bus system with twenty-three control variables are presented.

Keywords: Bing-Bang and Big-Crunch, FireFly, optimal power flow, discrete, continuous

NOTATIONS

F_T : total operating cost,NB: number of buses, NG: number of generator buses, NT: number of Transformers, NL: number of lines (branches),NSH: number of switchable shunts, NPQ: number of load buses NTR: number of transformers,P_i : active power injection at bus i,Q_i : reactive power at bus i,NP: population size (number of fireflies in FFO/number of Big-Bangs BB-BC)NC: number of control variables (co-ordinates of fireflies FF0/dispersions in BB-BC)

1. Introduction

Rapid growth in power system size and Electrical power demand, problem of reducing the operating cost has gained importance while maintaining voltage security and thermal limits of transmission line branches. A large number of mathematical programming (algorithms) and AI (Artificial Intelligence technique) have been applied to solve OPF[1,2]. In most general formulation, the OPF is a nonlinear, non-convex, large scale, static optimization problem with both continuous and discrete control Variables. Mathematical programming approaches such as Calculus methods, Non-linear programming (NLP), Linear programming (LP), Quadratic programming (QP), algorithms applied to obtain OPF solution require smooth and continuous cost function. Dynamic programming methods (DP) are good at solving quadratic and ramp cost functions, at the cost of increased dimensionality and may get struck in local optimality [3]. In cost optimization problems, it is desirable to obtain global optimum solution [2]. Recent advances in AI techniques can be applied as complementary approach to pave the way towards global/near global solutions for complex optimization problems such as OPF [2]. All search intelligence techniques, are population based and stochastic in nature. Search intelligence

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techniques developed by scientific community from the inspiration of natural social behaviour of different organisms/natural processes, offer multiple feasible solutions per iteration/generation. Genetic algorithms and its variants, Swarm intelligence, Bacteria foraging, ant-colony search techniques are applied to obtain quality solutions [4] to optimization problems. Big-Bang and Big-Crunch (BB-BC) developed by Erol and Eksin [5] from the concept of universal evolution, is also a population based search technique. BB-BC method has been proved to outperform genetic algorithm for benchmark test functions [5]. FireFly Optimization (FFO) also a heuristic algorithm that simulates the flashing behaviour of fireflies(lighting bugs) developed by Dr. Xin-she yang[6] has been applied to solve a number of complex optimization problems[7]. The conflicting objectives of Economic Load Dispatch (ELD) and thermal emission Pareto [8, 9] using traditional B_{mn} (real power loss coefficients) is solved by FFO. This paper aims at solving complex OPF problem with continuous and discrete control variables using BB-BC and FFO. Continuous variables are generator real power outputs and generator terminal voltages. Discrete variables are transformer tap settings and switchable shunts at power system buses. Each method is run 10 times with different initial control variables for 200 generations. The best results of each run are presented. Time taken by both optimization methods are compared along with reliability in arriving at quality solutions. Results of these two optimization methods are also compared with Genetic approaches available in literature [10, 11] of OPF for IEEE-30 bus system.

2. Optimal power flow problem formulation: OPF problem can be stated as follows

$$Min\ f(x,u) \tag{1}$$

$$S.t\ \ g(x,u) = 0 \tag{2}$$

$$h(x,u) \leq 0 \tag{3}$$

$$u \in U \tag{4}$$

$$\text{where } x = [\delta^T, V_L^T]^{\mathrm{T}} \tag{5}$$

x is a state vector of the system with bus bar angles δ and load bus voltages V_L.Control variables to optimize equation 1 are real power generation of generator loading units(P_g), terminal voltages of generators(V_g), tap-setting of transformers(t_{tap}) and switchable shunts(Q_{sh})

$$u = \left[P_g^T, V_g^T, t_{tap}^T, Q_{sh}^T\right] \tag{6}$$

Equation (1) is considered as sum of quadratic cost functions of thermal generating real power loading units with usual a_i,b_i,c_i cost coefficients of equation (7)

$$F_T(P_g) = \sum_{i=1}^{Ng} a_i + b_i P_{gi} + c_i P_{gi}^{\ 2} \ \$/\text{h} \tag{7}$$

subject to equality constraints of equation (2)

(i) active power balance in the network

P_i -$P_{gi} + P_{di} = 0$ (i=1, 2, 3,………NB)

(ii) reactive power balance in the network

Q_i -$Q_{gi} + Q_{di} = 0$ (i=NG+1,………NB)

U of equation 4 is feasible control vectors of inequality constraints ,they are

(i) active power generation of generator buses

$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}$ (i=1, 2,……… NG)

(ii) limits on voltage magnitudes of generator buses

$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max}$ (i=1, 2,…..NG)

(iii) limits on switchable shunts

$Q_{shi}^{min} \leq Q_{shi} \leq Q_{shi}^{max}$ (i=1,…..NSH)

(iv) limits on tap setting of transformers

$t_{tap}^{min} \leq t_{tap} \leq t_{tap}^{max}$ (i=1,…..NT)

Equation (3) has functional operating constraints which are as follows
(i) limits on reactive power generation of generator buses

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}$ (i=1, 2,……… NG)

(ii) limits on voltage magnitudes of load buses

$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}$ (i=NG+1,…….NB)

(iii) thermal limits of transmission lines

$|MVA|_i \leq MVA_i^{max}$ (i=1,…..NL)

The limits on the control variables of real power generations, voltage magnitudes of generators, transformer tap settings and switchable shunt devices are implicitly handled while generating the parameters randomly. Power flow solution to equation 2, results in state vectors x (bus bar angles, load bus voltages) of the power system network. The functional operating constraints are handled by a quadratic penalty function approach [12]. Due to inclusion of penalty terms, equation (7) transforms to a pseudo objective function (FF)

$$\min\ FF = F_T(P_g) + P_S + \sum_{i=1}^{NPQ} P_{Vi} + \sum_{i=1}^{NG} P_{Qi} + \sum_{i=1}^{NL} P_{Li} \qquad (8)$$

here P_S, P_{Vi}, P_{Qi}, P_{Li} are penalty terms for the slack bus generator MW limit violation, Load bus voltage limit violations, generator reactive power limit violations and violations for thermal limits of lines respectively.

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

Big-Bang and Big-crunch (BB-BC) optimization, is developed from the concept of universal evolution. Big-Bang Phase relates to energy dispersion in random state before evolution of universe. The dispersed energy is drawn into an order for the formation of universe. The stage of drawing the energy to an ordered state is Big-crunch phase. This concept can be mathematically simulated by obtaining object function values by creating random control variables (Big -Bang) phase. The Centre of Mass (CM) of Big-Bang phase is drawn into an ordered state by a Big- crunch phase. Crunch phase control variables emerge as best control variables from Big-Bang phase. Sequential repetition of Big-Bang around CM eventually leads to the global control variables of the function to be optimized. In the Big Bang phase control matrix (U) of dimension (NP*NC) is generated within lower and upper limits of control variables. Each row of control variable is substituted in function to be optimized to obtain NP number of function values. Then centre of mass u_{CM} of first phase dispersions can be computed using equation 9.

$$u_{CM} = \sum_{i=1}^{NP} (1/f^i) * u^i / (\sum_{i=1}^{NP} 1/f^i) \qquad (9)$$

Computation of u_{CM} is crunch phase of the optimization. In equation 9, u^i is i[th] row of U. f^i is the function value corresponding to u^i. This completes k[th] generation of optimization method. For (k+1)[th] generation, each row of control vector is updated around u_{CM} using equation 10.

$$u^i = u_{CM} + \left(u^{lmt} * randn\right)/k \qquad (10)$$

Where u^{lmt} is scale of upper U^{upper} and lower U^{lower} limits of the control variables, K is generation number, "randn" is normally distributed random number between -1 and +1. Repetition of Big Bang followed by crunch results in optimum value of the function.

4. Firefly Optimization (FFO)

Fireflies, randomly distributed in space, emit light due to photogenic organs on their surface for various social behaviour such as prey attraction, warning signals to a predator. The position of each firefly can be located using co-ordinate points. The brighter firefly emits more light to attract other fireflies. The other fireflies, which are lesser in brightness, get attracted towards brighter one, by updating their positions. Thus, fireflies keep moving in space till all of them reach same position (towards brighter one). This social behaviour of fireflies is mathematically simulated by introducing an attraction factor that depends on the position of Firefly. The brightness of firefly is proportional to the maximum of function to be optimized. The co-ordinates of each firefly are analogous to control variables of the optimization function to be optimized. The attraction towards brighter one is simulated as monotonically decreasing function.

$$\beta(r)=\beta_o \exp(-\gamma r^2) \tag{11}$$

In the above equation r is the distance between any two fireflies, β_o is the initial attractiveness and γ is an absorption co-efficient which controls the light intensity between two fireflies. The movement of firefly j, with row vector $u^{(j)}$ as co-ordinates can be moved to a more brighter firefly i , with row vector $u^{(i)}$ as co-ordinates by using the following update equation for firefly j ,

$$u^{(j)} = u^{(j)} + \beta_o \exp(-\gamma r^2).(u^{(i)} - u^{(j)}) + (\text{alpha*rand}(1, NC)\text{-}0.5) \tag{12}$$

Where "alpha" is step size, 'rand' is uniform random number between 0 and 1.In equation 12, first term is current position (co-ordinates) of firefly j, second term is the attractiveness factor and last term allows random movement of firefly. FFO is maximization algorithm. In this paper, in each generation of FFO, function values are sorted in descending order. Minimum of function value is considered as the brightest firefly, all other fireflies are moved to the brighter one as per equation 12. The implementation of optimization methods to OPF is presented in what follows.

5. Steps to implement BB-BC and FFO to OPF

In general evolutionary approach applied to OPF consists of similar steps, the specificity of approach differs only in updating the control variables from current generation to the new generation during optimal search. The following steps are common to both optimizations of this paper applied to solve OPF. The specificity of each optimization is indicated after the following steps.

1. Read OPF data (cost coefficients of objective function, Line, bus data and location of control variables) in power system network.
2. Generate initial control variable matrix U of size (NP*NC) within the lower and upper limit of control variables i.e i^{th} row of U can be generated as
   $u^i = U^{lower} *(U^{upper} - U^{lower})*\text{rand}(1, NC)$.
   Where, 'rand' is uniform random number [0, 1], U^{lower} and U^{upper} are lower and upper limits of control variables respectively . Typically, U^{lower} and U^{upper} are row vectors of dimension (1*NC).
3. Set generation count k=1.

4. Initialize FF count to 1. Row select of U to 1.
5. Fetch the row corresponding to Row select from U, modify line and bus data of power system network. Solve for power balance equation of OPF by using Newton Raphson (NR)/Fast decoupled load Flow (FDLF).
6. Check for functional operating constraints, for any violation of these constraints, activate penalties and Evaluate FF. set Row select=Row select +1, FF=FF+1, return to 5, till FF count=NP.
7. Store current best solution and its corresponding control variables. Check for stopping criteria, if met display current best solution, else go to step 8.
8. Update control variables in accordance with update Equation of respective optimization method. This step may result in violation of control variable limits. Those violated control variables should be made equal to their respective violated limit.
9. Set k=k+1.Return to step 3 till k=Maxgenrations.

In this paper, to satisfy power balance equations (step 5), FDLF is used [10]. During initial generations of optimization algorithm, FDLF may not converge even though control variables are within the range. For such cases, an additional large penalty term proportional to maximum real and reactive power mismatch is added to FF.FDLF maximum iterations and power balance mismatch tolerance are set to 8 and 0.001pu respectively. In step 8, control variables can be updated for BB-BC using equation 10 and for FFO using equation 12. While applying BB-BC, the minimum of FF value in each generation is considered as u_{CM} . Convergence criteria may be number of generations or difference between best function value of k^{th} and $(k+1)^{th}$ generation less than a specified tolerance. The above steps are implemented for the two test systems mentioned in this paper. The required code is written in MATLAB-7.0, as m-files using library routines of MATLAB soft ware. Code is executed on a 2.1 GHz, Pentium IV PC. The choice of optimization parameters namely NP (population size), alpha (step size), γ (absorption co-efficient), β_o(initial attraction) in FFO are presented along with test- case results.

6. Test Results and Discussions

To test the effectiveness and quality solutions of optimization methods of this paper, OPF simulations are carried on Ward-Hale- 6 bus and Modified IEEE-30 bus power system networks. Required data for the two systems for cost coefficients of generators, control variable limits, bus and transmission line data are taken from [13]. In both systems, first bus is slack bus and its real power limit is dealt in OPF using quadratic penalty. Generator voltages of slack bus for both systems are also included as control variables. Total system load considered for ward-Hale is (1.3500pu +j 0.3600pu) and for IEEE-30 bus system total base case load is (2.834pu+j1.2620pu). The lower and upper magnitudes of all load bus voltages are 0.95 pu and 1.05 pu respectively. The transformer tap setting is considered as (0.9+tap_ position*0.005), where tap_ position can take 41 discrete steps in the range 0 to 40 integer values. The tap_ position 0 indicates minimum tap 0.9 and tap_ position 40 indicates maximum tap of 1.1. Switchable shunt considered as (step _val*0.01), where step_ val can take 6 discrete steps in the range of 0 to 5 integer values, a step_ val 0 indicates 0.00pu capacitive shunt and 5 indicates capacitive shunt of 0.05pu(on 100MVA base).Test results for Ward-Hale and IEEE-30 bus systems are presented in table 1 and table 2 respectively . Each test case is run initially for base load (without optimization) with control variables as given in second column of the tables 1and 2. Cost after optimization by FF0 and BB-BC along with control variables and slack bus power is indicated in column 3 and column 4 of table 1, 2. Upon close observation of table 1, 2 optimal cost of real power generation obtained by BB-BC and FFO are almost same with a small edge for FF0.

Table 1. Variables for Ward-Hale 6 bus system

Variables	Base case	FFO	BB-BC
P_{g1}(pu)	1.2251	0.689885	0.689925
P_{g2}(pu)	0.25	0.8	0.8
V_{g1}(pu)	1.05	1.1	1.1
V_{g2}(pu)	1.10	1.15	1.15
Q_{sh4}(pu)	0.00	0.05	0.05
Q_{sh6}(pu)	0.00	0.05	0.05
$t_{1(6\text{-}5)}$	1.00	0.9550	0.9250
$t_{2(4\text{-}3)}$	1.00	0.9900	0.9800
Total real power generation(pu)	1.4753	1.4899	1.4899
Total real power losses (pu)	0.1253	0.1399	0.1399
cost($/hr)	**904.3086**	**450.9592**	**450.9907**

Table 2. Variables for IEEE 30- bus system

Variables	Base case	FFO	BB-BC
P_{g1}(pu)	0.987014	1.765171	1.749672
P_{g2}(pu)	0.8	0.487865	0.481406
P_{g5}(pu)	0.5	0.214746	0.208195
P_{g8}(pu)	0.2	0.216439	0.222772
P_{g11}(pu)	0.2	0.11980	0.14110
P_{g13}(pu)	0.2	0.120276	0.12000
V_{g1}(pu)	1.06	1.085421	1.087797
V_{g2}(pu)	1.043	1.066785	1.065492
V_{g5}(pu)	1.01	1.034902	1.03551
Vg11(pu)	1.082	1.069076	1.063822
V_{g13}(pu)	1.071	1.059076	1.010111
Q_{sh10}(pu)	0.19	0.04	0.04
Q_{sh12}(pu)	0	0.03	0.01
Q_{sh15}(pu)	0	0.02	0.02
Q_{sh17}(pu)	0	0.04	0.02
Q_{sh20}(pu)	0	0.04	0.02
Q_{sh21}(pu)	0	0.04	0.05
Q_{sh23}(pu)	0	0.03	0.04
Q_{sh24}(pu)	0.043	0.03	0.04
Q_{sh29}(pu)	0	0.02	0.02
$t_{1(6\text{-}9)}$	0.978	0.9850	1.0950
$t_{2(6\text{-}10)}$	0.969	0.9650	0.9600
$t_{3(4\text{-}12)}$	0.932	0.9900	1.0100
$t_{4(28\text{-}27)}$	0.968	1.005	1.015
Total Real power generation(pu)	2.887	2.9243	2.9231
Total Real power losses(pu)	0.053	0.0930	0.0891
Cost($/hr)	**900.5211**	**800.6803**	**800.8949**

Both optimization methods of this paper have only one common parameter, ‘NP’ to be chosen by trial. In case of BB-BC, NP is set to 25 and 50 for Ward-Hale and IEEE-30 bus case respectively. In case of FF0 other parameters of optimization update equation γ and β_o and are set to 1.The number of simulations carried out by keeping alpha constant for all generations of optimization process at different values in the range of 0.02 to unity, resulted in higher cost than BB-BC. To improve the results, alpha is reduced gradually in small steps as optimization proceeds number of generations. Such reduction of alpha is done by letting alpha=0.975*alpha, with alpha as unity before start of optimization generations. Trails made for alpha are indicated in table 3, with NP=25 in case of Ward-Hale, NP=40 in case of IEEE 30 bus system.

Table 3. Variation of alpha vs Cost

alpha	Ward-Hale Cost($/hr)	IEEE 30 Cost($/hr)
0.02	453.2976	802.747
0.5	451.9923	804.25
1	451.9234	807.171

Simulations carried out, by varying γ in the range 0.85 to 1,(β_o set to 1), after selection of proper step size alpha, also resulted in the optimal cost as reported in tables 1,2. Hence, from table 3 and simulation carried with variation of γ, selection of alpha is critical in FFO optimal cost. Step size alpha reduced in small steps in every generation lead to the local search of objective function. A comparative Convergence value of FF in $/hr is indicated in table 4. It is clear from table 4 that quality solutions can be arrived by both optimization methods in early generations of optimization. It can also be observed from table, that FF0 attains quality solutions than BB-BC, in very initial generations (20 generations). The reason can be attributed to the fact that FFO updates control variables in each generation based on distance norm between best function value of FF and the rest of function values among FF. In case of BB-BC, convergence to optimal value is controlled by k of equation 4. As optimization advances number of generations, BB-BC optimal search will be local as indicated in table 4. Table 5 indicates data statistics for ten independent test runs with different initial values, for 200 generations.

Table 4. A comparative converge values of FF.

Generation number	FFO	BB-BC
20	810.38	821.65
30	802.49	808.96
40	802.26	807.09
50	802.16	807.06
60	800.72	807.09
70	800.72	802.59
80	800.72	801.95
90	800.72	800.87
100	800.72	800.07

Computational time, difference between Maximum and Minimum cost, Mean cost and Standard deviations provided in Table 5 gives better edge to FFO compared to BB-BC. The best cost by application of problem specific advanced genetic operators[10], and real coded genetic algorithm[11] for same IEEE-30 bus system are 802.06 $/h and 801.824$/h respectively. Best cost obtained by both optimizations of this paper is less than genetic approaches. However, the proposed optimization approaches of this paper need to be tested for their robustness for certain complex non-linear and non-convex optimization situations like reactive power dispatch using recently proposed an Intelligent Water Drop (IWD) algorithm with target voltage stability index [14] and proposed two step-initialization heuristic search algorithm[15] to optimal power flow with FACTS devices.

Table 5. Minimum, Maximum, Mean and standard deviation with different initial values

	Ward-Hale		IEEE-30	
	FFO	BB-BC	FFO	BB-BC
Min ($/hr)	451	451	800.6	800.9
Max($/hr)	451.8	452.1	801.7	802.2
Mean ($/hr)	451.2	451.2	800.9	801.3
Standard deviation	0.3097	0.4469	0.353	0.4348
Meantime(S)	10.47	12.99	81.26	98.743

7. Conclusion

Big-Bang and Big-Crunch and firefly optimization methods are applied to solve complex static optimal power flow problem with continuous and discrete control variables. Test results and simulations carried towards establishing reliability confirm promising nature of the two-optimization methods for optimal power flow solutions. Careful selection of step size in Firefly optimization results in optimal, fast and reliable optimal power flow solutions than Big-Bang and Big-Crunch optimization. Both optimization methods are simple to implement compared to Genetic approaches for optimal power flow solutions.

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