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Amplified Black Hole Algorithm for Real Power Loss Reduction

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A B S T R A C T

This work presents Amplified Black Hole Algorithm (ABHA) for solving optimal reactive power problem. In the projected approach ABHA, Gravitational Search Algorithm (GSA) is merged with Black Hole Algorithm (BHA). Power loss reduction is the key objective in the proposed work. The gravitational force between stars and the progression of stars to the black hole is attuned while explore the solution space. Assumption made that heavy objects are stars in a gravitational system, which become black holes and the exploitation of GSA is enhanced. During the progression of the projected algorithm, the radius of the black hole diminishes and more objects are included, which assist to stop early convergence. To improve the exploration and exploitation, stars gravity information has been utilized. During the progression of the projected algorithm, the radius of the black hole diminishes, and more objects are included, which assist to stop early convergence. Some of the most excellent objects turn out to be the black hole, affect other objects by their sturdy gravity. The other objects are alienated into two groups: Heavy agents and light agents. Proposed ABHA has been tested in standard IEEE 14, 30, 57, 118, 300 bus test systems and simulation results show the projected algorithm reduced the real power loss comprehensively.

Keywords: Optimal reactive power, Transmission loss, Amplified black hole.

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1. Introduction

Reactive power problem plays a key role in secure and economic operations of power system. Optimal reactive power problem has been solved by variety of types of methods [1-6]. Nevertheless numerous scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-15] are applied to solve the reactive power problem, but the main problem is many algorithms get stuck in local optimal solution and failed to balance the Exploration and Exploitation during the search of global solution. In this paper, Amplified Black Hole Algorithm (ABHA) has been applied to solve optimal reactive power problem. Real power loss reduction is the key objective of the problem. In Black Hole Algorithm

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(BHA), due to over time, exploration is condensed and exploitation capabilities weaken such that algorithm amend itself in semi-optimal points. Balance between exploration and exploitation is needed to keep black hole algorithm protected from being trapped in local optima. In Gravitational Search Algorithm (GSA), there is a chance of early convergence at many instants for various problems. Since the directing force exert a pull on the objects to each other, GSA performance diminishes when the objects converge to a non-optimal solution, and mainly GSA suffer from sluggish search speed in the final iterations. In the projected ABHA, GSA is merged with BHA. The gravitational force between stars and the progression of stars to the black hole is attuned while explore the solution space. Distance between a candidate solution and black hole (most excellent candidate) is less than the value of "R" that specified candidate will get shrunken and a new-fangled candidate is produced which dispersed arbitrarily in the exploration space. Assumption made that heavy objects are stars in a gravitational system, which become black holes, and exploitation of GSA is enhanced. During the progression of the projected algorithm, the radius of the black hole diminishes and more objects are included, which assist to stop early convergence. Proposed ABHA has been tested in standard IEEE 14, 30, 57, 118, 300 bus test systems and simulation results show the projected algorithm reduced the real power loss comprehensively.

2. Problem Formulation

Objective of the problem is to reduce the true power loss:

$$F = P_L = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right). \quad (1)$$

Voltage deviation given as follows:

$$F = P_L + \omega_v \times \text{Voltage Deviation}. \quad (2)$$

Voltage deviation given by:

$$\text{Voltage Deviation} = \sum_{i=1}^{Npq} |V_i - 1|. \quad (3)$$

Constraint (Equality):

$$P_G = P_D + P_L. \quad (4)$$

Constraints (Inequality):

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max}. \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g. \quad (6)$$

$$V_i^{min} \le V_i \le V_i^{max}, i \in N. \quad (7)$$

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T. \quad (8)$$

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C. \quad (9)$$

3. Black Hole Algorithm

In BHA, the evolution of the population is through pushing the candidates in the course of the most excellent candidate in iterations and black hole which swap with those in the search space. Production of population is capricious and in the exploration space candidates, the stars are present [16].

Incorporation of stars by the black hole is given as

$$Y_i(t+1) = Y_i(t) + \text{random} \times \left(Y_{BH} -, Y_i(t)\right) \; i = 1,2,..,N. \qquad \textbf{\textit{(10)}}$$

Event horizon radius of black hole algorithm is computed as

$$R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i}. \qquad \textbf{\textit{(11)}}$$

Distance between a candidate solution and black hole (most excellent candidate) is less than the value of R that specified candidate will get shrunken and a new-fangled candidate is produced which dispersed arbitrarily in the exploration space.

To improve the exploration and exploitation, stars gravity information has been utilized. Gravitational forces between the stars are definite and progression of stars towards the black hole is accustomed during the incursion in solution space.

The location of the ith stars (Y_i) is given by

$$Y_i = (\text{star}_i, \dots, \text{star}_N, \text{blcakhole}_d). \qquad \textbf{\textit{(12)}}$$

At time "t", the incorporation of star "i" from star "j" is defined as

$$E_{ij}^{d} = \xi(t_o) \frac{C_{pi}(t) \times C_{aj}(t) \times \left(\text{star}_j(t) - \text{star}_i(t)\right)}{\left(D_{ij}(t) + \varepsilon\right)^2 \times \left(C_{pi}(t) + C_{aj}(t)\right)} \times \left(\frac{t_o}{t - t_o}\right)^a. \qquad \textbf{\textit{(13)}}$$

Complete force is randomly weighted by

$$E_i^d(t) = \sum_{j=1\, J \neq i}^{N} \text{random}_i E_{ij}^d(t). \qquad \textbf{\textit{(14)}}$$

Speeding up of the star i at time t, in direction dth, is given as

$$a_i^d(t) = \frac{E_i^d(t)}{C_{ii}(t)}. \qquad \textbf{\textit{(15)}}$$

Position and velocity are calculated by

$$v_i^d(t+1) = \text{random}_i \times v_i^d(t) + a_i^d(t). \qquad \textbf{\textit{(16)}}$$

$$\text{star}_i(t+1) = \text{star}_i(t) + v_i^d(t+1). \qquad \textbf{\textit{(17)}}$$

- Population of stars are initialized with capricious locations in the search space loop.
- Objective function value for each star has been calculated.
- Star which possesses most excellent fitness value is chosen as black hole.

- Position of every star is modified by $Y_i(t+1) = Y_i(t) + \text{random} \times (Y_{BH} -, Y_i(t))\ i = 1,2,..,N$.
- Black hole, superior to a star location, exchanges the locations.
- In event horizon, a star cross black hole replaces with a new star in capricious location in exploration space.
- If an end condition is met, egress the loop.

Arbitrarily engender the Np target vectors $Y_i^g = (i = 1,2..,N_P)$. Target vector with the most excellent fitness value is selected as black hole Y_{BH}^0. Put the utmost generation number as gmax.

Mutation and cross over is calculated by

$$M_i^{g+1} = Y_{r1}^g + F \times (Y_{r2}^g - Y_{r3}^g), r1 \neq r2 \neq r3 \neq i,$$

$$H_{i,j}^{g+1} = \begin{cases} M_i^{g+1} \text{ if } (\text{rand}_j(0,1) \leq C_r) \\ Y_{i,j}^g \quad \text{otherwise} \end{cases}.$$

Position, velocity are calculated by

$$v_i^d(t+1) = \text{random}_i \times v_i^d(t) + a_i^d(t),$$

$$\text{star}_i(t+1) = \text{star}_i(t) + v_i^d(t+1).$$

Endurance criterion calculated by

$$Y_i^{g+1} = \begin{cases} u_i^{g+1} \ f(u_i^{g+1}) \leq f(b_i^{g+1}) \\ b_i^{g+1} \ f(u_i^{g+1}) \leq f(b_i^{g+1}) \end{cases}.$$

Vector correction is done through

$$\|Y_i^{g+1} - Y_{BH}^{g+1}\| < R$$

If maximum generation g_{max} is attained, then stop, or else, go to Step 2.

4. Gravitational Search Algorithm

GSA is based on the Newton's law of gravitation [17]. Two particles in the universe attract each other with a force in the direction of the middle line. It mathematically is expressed as

$$F = G\frac{M_1 M_2}{R^2}. \quad \textbf{\textit{(18)}}$$

Attractiveness defined by

$$F_{ij}^d(t) = G(t)\frac{M_{Pi}(t)}{R_{ij}(t)+\varepsilon}(x_j^d(t) - x_i^d(t)). \quad \textbf{\textit{(19)}}$$

Gravitational constant given by

$$G(t) = G_o e^{-\alpha\frac{t}{T}}. \quad \textbf{\textit{(20)}}$$

Gravity of the surrounding particles is calculated by

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} \text{rand} \times F_{ij}^d(t). \qquad (21)$$

Acceleration of particle is calculated by

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}. \qquad (22)$$

Inertial mass of the particle is computed by

$$M_{ai} = M_{pi} = M_{ii} = M_i, \ (i = 1, 2, 3.., N). \qquad (23)$$

$$m_i(t) = \frac{fit_i(t) - worst\,(t)}{best\,(t) - worst\,(t)}. \qquad (24)$$

$$m_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}. \qquad (25)$$

Best and worst value were found out after population updating by

$$best(t) = \underbrace{\min}_{j\in\{1,.,N\}} fit_j(t). \qquad (26)$$

$$worst(t) = \underbrace{\max}_{j\in\{1,.,N\}} fit_j(t). \qquad (27)$$

Velocity and position update is done through

$$V_i^d(t+1) = \text{rand} \times V_i^d(t) + a_i^d(t). \qquad (28)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t). \qquad (29)$$

Where rand is a random number from [0, 1], V_i^d(t), and x_i^d (t), respectively represents the speed and position proportion at dimension d of particle i at time t.

- Step a: Arbitrarily initialize the population and position.
- Step b: Optimum solution obtained by $best(t) = \underbrace{\min}_{j\in\{1,.,N\}} fit_j(t)$.
- Step c: Mutation triggered by $TR_i^t = e^{\left(-\frac{dim}{2}\times\frac{t}{T}\right)} \times \left(\text{random} \times e^{\left(-\frac{i-1}{N}\right)} + \varepsilon\right)$ determines whether each particle is variant or not. Once it met conditions of the mutation, then the mutation process is carried out with reference to $x_t(t) = (1+r)x_t(t)$ and random $\leq \left(1-\frac{t}{T}\right)$, $x_i(t) = MLN_i(t)x_i(t)$, random $> \left(1-\frac{t}{T}\right)$ or else mutation doesn't occur.
- Step d: Best and worst value found out after population updating is done by $best(t) = \underbrace{\min}_{j\in\{1,.,N\}} fit_j(t)$ and $worst(t) = \underbrace{\max}_{j\in\{1,.,N\}} fit_j(t)$.
- Step e: Inertia mass of the particle M is computed by $M_{ai} = M_{pi} = M_{ii} = M_i$, (i= 1, 2, 3,, N) $m_i(t) = \frac{fit_i(t) - worst\,(t)}{best\,(t) - worst\,(t)}$ and $m_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}$.
- Step f: Gravity of the surrounding particles is calculated by $F_i^d(t) = \sum_{j=1, j\neq i}^{N} \text{rand} \times F_{ij}^d(t)$y.

- Step g: Accelerated velocity of the particles is found by $a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}$ and velocity of the particle is obtained by $V_i^d(t+1) = \text{rand} \times V_i^d(t) + a_i^d(t)$.
- Step h: Position of the particle is modernized by $x_i^d(t+1) = x_i^d(t) + v_i^d(t)$.
- Step i: Back to the Step b loop iteration until the cycle index or obligatory exactitude is reached.
- Step j: Stop the sequence and output the result.

5. Amplified Black Hole Algorithm

In BHA, due to over time, exploration is condensed and exploitation capabilities weaken such that algorithm amend itself in semi-optimal points. Balance between exploration and exploitation is needed to keep black hole algorithm protected from being trapped in local optima. In GSA, there is a chance of early convergence at many instants for various problems. Since the directing force exert a pull on the objects to each other, GSA performance diminishes when the objects converge to a non-optimal solution, and mainly GSA suffer from sluggish search speed in the final iterations. In the projected ABHA, GSA is merged with BHA. The gravitational force between stars and the progression of stars to the black hole is attuned while explore the solution space. Distance between a candidate solution and black hole (most excellent candidate) is less than the value of "R" that specified candidate will get shrunken and a new-fangled candidate is produced which dispersed arbitrarily in the exploration space. Assumption made that heavy objects are stars in a gravitational system, which become black holes, and exploitation of GSA is enhanced. During the progression of the projected algorithm, the radius of the black hole diminishes and more objects are included, which assist to stop early convergence.

Some of the most excellent objects turn out to be the black hole, affect other objects by their sturdy gravity. The other objects are alienated from two groups: heavy agents and light agents. The position and velocity of the heavy agents and light agents are updated by

$$V_i^d(t+1) = \text{rand} \times V_i^d(t) + a_i^d(t) \text{ and } x_i^d(t+1) = x_i^d(t) + v_i^d(t).$$

Engender the preliminary population.

Compute the fitness value.

Modernize the G, most excellent, and poor in the population.

Compute "M" and "a" for each agent.

Renew the velocity and position.

Is end criterion is met? if "yes" return with best solution or else go to step b.

End.

6. Simulation Results

At first in standard IEEE 14 bus system the validity of the proposed ABHA has been tested, ***Table 1*** shows the constraints of control variables; ***Table 2*** shows the limits of reactive power generators, and the comparison results are presented in ***Table 3***.

Table 1. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 14 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 2. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 14 Bus	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

Table 3. Simulation results of IEEE −14 system.

Control Variables	Base case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	ABHA
$VG-1$	1.060	1.100	1.100	NR*	NR*	1.002
$VG-2$	1.045	1.085	1.086	1.029	1.060	1.009
$VG-3$	1.010	1.055	1.056	1.016	1.036	1.002
$VG-6$	1.070	1.069	1.067	1.097	1.099	1.009
$VG-8$	1.090	1.074	1.060	1.053	1.078	1.011
Tap 8	0.978	1.018	1.019	1.04	0.95	0.918
Tap 9	0.969	0.975	0.988	0.94	0.95	0.909
Tap 10	0.932	1.024	1.008	1.03	0.96	0.914
$QC-9$	0.19	14.64	0.185	0.18	0.06	0.142
PG	272.39	271.32	271.32	NR*	NR*	271.46
QG (Mvar)	82.44	75.79	76.79	NR*	NR*	75.92
Reduction in PLoss (%)	0	9.2	9.1	1.5	2.5	18.6
Total PLoss (Mw)	13.550	12.293	12.315	13.346	13.216	11.021

NR* - Not reported.

Then the proposed ABHA has been tested, in IEEE 30 Bus system. ***Table 4*** shows the constraints of control variables, ***Table 5*** shows the limits of reactive power generators and the comparison results are presented in ***Table 6***.

Table 4. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 30 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 5. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 30 Bus	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

Table 6. Simulation results of IEEE −30 system.

Control Variables	Base Case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	ABHA
$VG{-}1$	1.060	1.101	1.100	NR*	NR*	1.012
$VG{-}2$	1.045	1.086	1.072	1.097	1.094	1.004
$VG{-}5$	1.010	1.047	1.038	1.049	1.053	1.002
$VG{-}8$	1.010	1.057	1.048	1.033	1.059	1.019
$VG{-}12$	1.082	1.048	1.058	1.092	1.099	1.024
VG-13	1.071	1.068	1.080	1.091	1.099	1.031
Tap11	0.978	0.983	0.987	1.01	0.99	0.929
Tap12	0.969	1.023	1.015	1.03	1.03	0.904
Tap15	0.932	1.020	1.020	1.07	0.98	0.912
Tap36	0.968	0.988	1.012	0.99	0.96	0.908
QC10	0.19	0.077	0.077	0.19	0.19	0.090
QC24	0.043	0.119	0.128	0.04	0.04	0.101
PG (MW)	300.9	299.54	299.54	NR*	NR*	297.4
QG (Mvar)	133.9	130.83	130.94	NR*	NR*	131.35
Reduction in PLoss (%)	0	8.4	7.4	6.6	8.3	14.3
Total PLoss (Mw)	17.55	16.07	16.25	16.38	16.09	15.04

NR* - Not reported.

Then the proposed ABHA has been tested in IEEE 57 bus system. ***Table 7*** shows the constraints of control variables; ***Table 8*** shows the limits of reactive power generators and the comparison results are presented in ***Table 9***.

Table 7. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 57 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 8. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 57 Bus	1	-140	200
	2	-17	50
	3	-10	60
	6	-8	25
	8	-140	200
	9	-3	9
	12	-150	155

Table 9. Simulation results of IEEE −57 system.

Control Variables	Base Case	MPSO [19]	PSO [19]	CGA [19]	AGA [19]	ABHA
VG 1	1.040	1.093	1.083	0.968	1.027	1.009
VG 2	1.010	1.086	1.071	1.049	1.011	1.023
VG 3	0.985	1.056	1.055	1.056	1.033	1.041
VG 6	0.980	1.038	1.036	0.987	1.001	1.012
VG 8	1.005	1.066	1.059	1.022	1.051	1.035
VG 9	0.980	1.054	1.048	0.991	1.051	1.032
VG 12	1.015	1.054	1.046	1.004	1.057	1.042
Tap 19	0.970	0.975	0.987	0.920	1.030	0.901
Tap 20	0.978	0.982	0.983	0.920	1.020	0.901
Tap 31	1.043	0.975	0.981	0.970	1.060	0.900
Tap 35	1.000	1.025	1.003	NR*	NR*	1.010
Tap 36	1.000	1.002	0.985	NR*	NR*	1.012
Tap 37	1.043	1.007	1.009	0.900	0.990	1.001
Tap 41	0.967	0.994	1.007	0.910	1.100	0.946
Tap 46	0.975	1.013	1.018	1.100	0.980	1.014
Tap 54	0.955	0.988	0.986	0.940	1.010	0.928
Tap 58	0.955	0.979	0.992	0.950	1.080	0.931
Tap 59	0.900	0.983	0.990	1.030	0.940	0.923
Tap 65	0.930	1.015	0.997	1.090	0.950	1.001
Tap 66	0.895	0.975	0.984	0.900	1.050	0.930
Tap 71	0.958	1.020	0.990	0.900	0.950	1.001
Tap 73	0.958	1.001	0.988	1.000	1.010	1.014
Tap 76	0.980	0.979	0.980	0.960	0.940	0.948
Tap 80	0.940	1.002	1.017	1.000	1.000	1.001
QC 18	0.1	0.179	0.131	0.084	0.016	0.151
QC 25	0.059	0.176	0.144	0.008	0.015	0.140
QC 53	0.063	0.141	0.162	0.053	0.038	0.121
PG (MW)	1278.6	1274.4	1274.8	1276	1275	1272.06
QG (Mvar)	321.08	272.27	276.58	309.1	304.4	272.46
Reduction in PLoss (%)	0	15.4	14.1	9.2	11.6	23.02
Total PLoss (Mw)	27.8	23.51	23.86	25.24	24.56	21.4

NR* - Not reported.

Then the proposed ABHA has been tested in IEEE 118 bus system. ***Table 10*** shows the constraints of control variables and comparison results are presented in ***Table 11***.

Table 10. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 118 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 11. Simulation results of IEEE −118 system.

Control Variables	Base Case	MPSO [19]	PSO [19]	PSO [19]	CLPSO [19]	ABHA
VG 1	0.955	1.021	1.019	1.085	1.033	1.010
VG 4	0.998	1.044	1.038	1.042	1.055	1.015
VG 6	0.990	1.044	1.044	1.080	0.975	1.020
VG 8	1.015	1.063	1.039	0.968	0.966	1.014
VG 10	1.050	1.084	1.040	1.075	0.981	1.010
VG 12	0.990	1.032	1.029	1.022	1.009	1.021
VG 15	0.970	1.024	1.020	1.078	0.978	1.016
VG 18	0.973	1.042	1.016	1.049	1.079	1.004
VG 19	0.962	1.031	1.015	1.077	1.080	1.010
VG 24	0.992	1.058	1.033	1.082	1.028	1.011
VG 25	1.050	1.064	1.059	0.956	1.030	1.010
VG 26	1.015	1.033	1.049	1.080	0.987	1.026
VG 27	0.968	1.020	1.021	1.087	1.015	0.900
VG31	0.967	1.023	1.012	0.960	0.961	0.901
VG 32	0.963	1.023	1.018	1.100	0.985	0.909
VG 34	0.984	1.034	1.023	0.961	1.015	1.010
VG 36	0.980	1.035	1.014	1.036	1.084	1.002
VG 40	0.970	1.016	1.015	1.091	0.983	0.952
VG 42	0.985	1.019	1.015	0.970	1.051	1.002
VG 46	1.005	1.010	1.017	1.039	0.975	1.014
VG 49	1.025	1.045	1.030	1.083	0.983	1.018
VG 54	0.955	1.029	1.020	0.976	0.963	0.910
VG 55	0.952	1.031	1.017	1.010	0.971	0.927
VG56	0.954	1.029	1.018	0.953	1.025	0.948
VG 59	0.985	1.052	1.042	0.967	1.000	0.937
VG 61	0.995	1.042	1.029	1.093	1.077	0.912
VG 62	0.998	1.029	1.029	1.097	1.048	0.929
VG 65	1.005	1.054	1.042	1.089	0.968	1.003
VG 66	1.050	1.056	1.054	1.086	0.964	1.042
VG 69	1.035	1.072	1.058	0.966	0.957	1.019
VG 70	0.984	1.040	1.031	1.078	0.976	1.014
VG 72	0.980	1.039	1.039	0.950	1.024	1.002
VG 73	0.991	1.028	1.015	0.972	0.965	1.000
VG 74	0.958	1.032	1.029	0.971	1.073	1.001
VG 76	0.943	1.005	1.021	0.960	1.030	1.004
VG 77	1.006	1.038	1.026	1.078	1.027	1.001
VG 80	1.040	1.049	1.038	1.078	0.985	1.000
VG 85	0.985	1.024	1.024	0.956	0.983	1.017
VG 87	1.015	1.019	1.022	0.964	1.088	1.008

Control Variables	Base Case	MPSO [19]	PSO [19]	PSO [19]	CLPSO [19]	ABHA
VG 89	1.000	1.074	1.061	0.974	0.989	1.030
VG 90	1.005	1.045	1.032	1.024	0.990	1.011
VG 91	0.980	1.052	1.033	0.961	1.028	1.002
VG 92	0.990	1.058	1.038	0.956	0.976	1.016
VG 99	1.010	1.023	1.037	0.954	1.088	1.002
VG 100	1.017	1.049	1.037	0.958	0.961	1.009
VG 103	1.010	1.045	1.031	1.016	0.961	1.001
VG 104	0.971	1.035	1.031	1.099	1.012	1.010
VG 105	0.965	1.043	1.029	0.969	1.068	1.021
VG 107	0.952	1.023	1.008	0.965	0.976	1.004
VG 110	0.973	1.032	1.028	1.087	1.041	1.003
VG 111	0.980	1.035	1.039	1.037	0.979	1.010
VG 112	0.975	1.018	1.019	1.092	0.976	1.090
VG 113	0.993	1.043	1.027	1.075	0.972	1.010
VG 116	1.005	1.011	1.031	0.959	1.033	1.004
Tap 8	0.985	0.999	0.994	1.011	1.004	0.930
Tap 32	0.960	1.017	1.013	1.090	1.060	1.000
Tap 36	0.960	0.994	0.997	1.003	1.000	0.942
Tap 51	0.935	0.998	1.000	1.000	1.000	0.910
Tap 93	0.960	1.000	0.997	1.008	0.992	1.002
Tap 95	0.985	0.995	1.020	1.032	1.007	0.939
Tap 102	0.935	1.024	1.004	0.944	1.061	1.016
Tap 107	0.935	0.989	1.008	0.906	0.930	0.939
Tap 127	0.935	1.010	1.009	0.967	0.957	1.018
QC 34	0.140	0.049	0.048	0.093	0.117	0.012
QC 44	0.100	0.026	0.026	0.093	0.098	0.020
QC 45	0.100	0.196	0.197	0.086	0.094	0.118
QC 46	0.100	0.117	0.118	0.089	0.026	0.107
QC 48	0.150	0.056	0.056	0.118	0.028	0.024
QC 74	0.120	0.120	0.120	0.046	0.005	0.118
QC 79	0.200	0.139	0.140	0.105	0. 148	0.102
QC 82	0.200	0.180	0.180	0.164	0.194	0.148
QC 83	0.100	0.166	0.166	0.096	0.069	0.100
QC 105	0.200	0.189	0.190	0.089	0.090	0.112
QC 107	0.060	0.128	0.129	0.050	0.049	0.123
QC 110	0.060	0.014	0.014	0.055	0.022	0.001
PG(MW)	4374.8	4359.3	4361.4	NR*	NR*	4358.1
QG(MVAR)	795.6	604.3	653.5	* NR*	NR*	605.3
Reduction in PLOSS(%)	0	11.7	10.1	0.6	1.3	13.3
Total PLOSS (Mw)	132.8	117.19	119.34	131.99	130.96	115.04

NR* - Not reported.

Then IEEE 300 bus system [18] is used as test system to validate the performance of the ABHA. ***Table 12*** shows the comparison of real power loss obtained after optimization.

Table 12. Comparison of real power loss.

Parameter	Method EGA [21]	Method EEA [21]	Method CSA [20]	ABHA
PLOSS (MW)	646.2998	650.6027	635.8942	613.2486

7. Conclusions

In ABHA successfully was solved the optimal reactive power problem. In the projected approach ABHA, the GSA is merged with BHA. Gravitational forces between the stars are definite and progression of stars towards the black hole is accustomed during the incursion in solution space. During the progression of the projected algorithm, the radius of the black hole diminishes and more objects are included, which assisted to stop the early convergence. Proposed ABHA has been tested in standard IEEE 14, 30, 57, 118, 300 bus test systems and simulation results show the projected algorithm reduced the real power loss comprehensively. In future application of the projected algorithm, it can be applied to practical test systems.

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