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Research Article

Real Power Loss Reduction by Improved Glow Worm Swarm, Cognitive Development, Black Hole and Enhanced Bat Algorithms

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ABSTRACT

This paper proposes an Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) to solve the optimal reactive power problem. Glow worm swarm optimization (GSO) algorithm is a new algorithm which stimulated from the light emission behavior of glow worms to attract prey. GSO algorithm has limitation in global search, short fall in accuracy computation and often falls into local optimum. In order to prevail over the above said shortcomings of GSO, this work presents improved GSO algorithm, to solve the problem. Glow worm Swarm Optimization Algorithm incorporated with the parallel hybrid mutation which unites the uniform distribution mutation with the Gaussian distribution mutation. In proposed (IGSO) algorithm dynamic moving step length is implemented to each individual. When the position unchanged in any generation then Normal distribution variation to the glow worm is applied. Then in this paper Cognitive Development Optimization (CDO) algorithm utilized for solving reactive power problem. Piaget's Theory on Cognitive Development, which has; maturation, social interaction, balancing; all these three processes are utilized throughout the new learning phase and improving constantly the cognitive infrastructure. Then this work presents Black Hole Algorithm (BHA) for solving optimal reactive power problem. Evolution of the population is through push the candidates in the itinerary of the most exceptional candidate in iterations and black hole which exchange with those in the exploration space. Tremendous candidate amongst all the candidates in iterations is selected as a black hole and left over candidates structured as the standard stars. Black hole formation is not capricious but it is form as genuine candidates of the created population. 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. Then in this paper Bat Algorithm with Combination of Numerous Schemes (BACS) is proposed to solve optimal reactive power problem. Bat algorithm is mimicked from the actions of the Bat; mainly time delays are used for emission to reflection and employ it for navigation. The global convergence capability of the algorithm becomes weaker when the progress of operator increases and when the exploration operator augments, then the convergence accurateness will be inadequate. Consequently, in this paper, numerous schemes have been selected to solve the problem and it work as autonomous selection strategy. In the proposed algorithm different individuals prefer different strategy to modernize the position with reference to the quality of fitness. Proposed Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) has been tested in standard IEEE 14, 30,300 bus test system and simulation results show the projected algorithm reduced the real power loss considerably.

Keywords: Optimal reactive power; Transmission loss; Glow worm swarm optimization; Cognitive development optimization; Black hole; Bat algorithm

INTRODUCTION

Reactive power problem plays an important role in secure and economic operations of power system. Numerous types of methods [1-6] have been utilized to solve the optimal reactive power problem. However many scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-16] are applied to solve the reactive power problem. This paper proposes a Proposed Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA)

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and Bat Algorithm with Combination of Numerous Schemes (BACS) to solve the optimal reactive power problem. Glow worm Swarm Optimization (GSO) algorithm is a new algorithm which stimulated from the light emission behavior of glow worms to attract prey. GSO algorithm has limitation in global search, short fall in accuracy computation and often falls into local optimum. In order to prevail over the above said shortcoming of GSO, this work presents improved GSO algorithm, to solve the problem. Glow worm Swarm Optimization Algorithm incorporated with the parallel hybrid mutation which unites the uniform distribution mutation with the Gaussian distribution mutation. In proposed (IGSO) algorithm dynamic moving step length is implemented to each individual. When the position unchanged in any generation then Normal distribution variation to the glow worm is applied. Then in this paper Cognitive Development Optimization (CDO) algorithm utilized for solving reactive power problem. Piaget's Theory on Cognitive Development, which has; maturation, social interaction, balancing; all these three processes are utilized throughout the new learning phase and improving constantly the cognitive infrastructure. In this paper, Black Hole Algorithm (BHA) has been applied to solve optimal reactive power problem. 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. Excellent candidate amongst all the candidates in iterations is chosen as a black hole and remaining candidates structured as the standard stars. Black hole formation is not capricious but it is form as genuine candidates of the created population. Towards the black hole, all the candidates are stimulated grounded on their present location with a random number. Production of population is capricious and in the exploration space candidates, stars are present. 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. Then this paper proposes Bat Algorithm with Combination of Numerous Schemes (BACS) to solve optimal reactive power problem. Bat algorithm is mimicked from the actions of the Bat; mainly time delays are used for emission to reflection and employ it for navigation. In the projected Bat Algorithm with Combination of Numerous Schemes (BACS) many operators take part to decide about the convergence ability of the algorithm. The global convergence capability of the algorithm becomes weaker when the progress of operator increases and when the exploration operator augments, then the convergence accurateness will be inadequate. Consequently, in this paper, numerous schemes have been selected to solve the problem and it work as autonomous selection strategy. In the proposed algorithm different individuals prefer different strategy to modernize the position with reference to the quality of fitness. Proposed Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) has been tested in standard IEEE 14, 30,300 bus test system and simulation results show the projected algorithm reduced the real power loss considerably.

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)

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

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

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

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

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

Improved glow worm swarm optimization algorithm

In the Glow worm Swarm Optimization GSO algorithm, glow-worms are randomly spread in the search space; glow-worms bear a luminescent quantity called Lucifer in along with them and they have their own decision domain $r_d^i = \left(0 < r_d^i \le r_s\right)$. Four stages are plays vital role in basic algorithm [17]: initial distribution of glow-worms, Lucifer in modernizing segment, Movement segment, and Neighborhood range renewal segment.

Lucifer in-update is given by,

$$l_i(t) = (1-\rho) I_i(t-I) + \gamma J(x_i(t)) \quad (10)$$

In movement phase, each glow worm chooses a neighbour and then shifts toward it with a certain probability and defined by,

$$P_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_{i(t)}} l_k(t) - l_i(t)} \quad (11)$$

After the movement, Glow worm's location is modernized by,

$$x_i(t+1) = x_i(t) + st^* \left(\frac{x_j(t) - x_i(t)}{x_j(t) - x_i(t)} \right) \quad (12)$$

The neighbourhood range modernization by,

$$r_d^i(t+1) = min\left\{ r_s, max\left\{ 0, r_d^i(t) + \beta\left(n_t - |N_i(t)|\right) \right\} \right\} \quad (13)$$

In the projected improved Glow worm Swarm Optimization Algorithm (IGSO) enhancement algorithm has been done by intermingling Glow worm Swarm Optimization Algorithm with the parallel hybrid mutation which unites the uniform distribution mutation with the Gaussian distribution mutation.

Fix the mutation ability value of each individual is given by:

$$mc_i = 0.050 + 0.450 \frac{\left(exp\left(\frac{5(i-1)}{(ps-1)} \right) - 1 \right)}{\exp(5) - 1} \quad (14)$$

Dynamic moving step size approach can accelerate the convergence speed in the algorithm at preliminary period and perk up the computation accurateness in the algorithm later phase;

$$s(t) = st * \left(1 - \frac{t}{generation} \right) + 10^{-s} \quad (15)$$

In the projected algorithm, glow worm will be put on to the normal distribution variation by the equation (16) when its position is not changed in any generation.

$$x_i(t+1) = normal\ random\left(0, st(t) * x_i(t)\right) \quad (16)$$

Fix the number of dimensions=m

Fix the number of glow worms=n

Consider "s" be the step size

Let x_i (t) be the position of glow worm "i" at time "t"

Glow worm distribution segment;

For i=1 to n do $l_i(0)=l_0$

$r_i^d = r_s$

Fix maximum iteration number=iter_max;

Fix t=1;

While (t<=iter_max) do:

{

For every glow worm i do:

Luciferin modernized by $l_i(t)=(1-\rho)l_i(t-1)+\gamma J(x_i(t))$

For every glow worm i do:

{

Validate the set of neighbours by $P_{ij}(t)=\frac{l_j(t)-l_i(t)}{\sum_{k\in N_{i(t)}} l_k(t)-l_i(t)}$

Calculate the probability of movement by $x_i(t+1)=x_i(t)+st^*\left(\frac{x_j(t)-x_i(t)}{x_j(t)-x_i(t)}\right)$

Choose a neighbour and update neighbourhood range by $r_d^i(t+1)=min\{r_s, max\{0, r_d^i(t)+\beta(n_t-|N_i(t)|)\}\}$

if the position of glow worm" i" is not modified then normal distribution variation by

$x_i(t+1)=normal\,random(0, st(t)*x_i(t))$

}

For i=1:ps

If ceil(mci+random-1)==1

If random<=pu

Xi(t)=(1+random)*Xi(t)

Else

Xi(t)=Gaussian( )*Xi(t)

End if

End

t=t+1;

}

Cognitive development optimization algorithm

Cognitive Development Optimization (CDO) algorithm is inspired from Piaget's Theory on Cognitive Development [18-19]. Piaget's Theory on Cognitive Development, which has; maturation, social interaction, balancing; all these three processes are utilized throughout the new learning phase and improving constantly the cognitive infrastructure.

Step 1 Initial stage: Set preliminary parameters

Step 2: particles are placed arbitrarily, fitness value is calculated and position are updated.

most excellent_particle_it_(new)=most excellent_particle_it_(existing)+(arbitrary*most excellent_particle_it_(existing)) (17)

Where, it-initial interactivity rate.

Step 3: Loops are repeated until maximum condition reached.

Step 3.1: Socialization stage:

Particles "it" values are modernized in arbitrary mode.

$Particle_j\_it\_(new)=Particle_j\_it\_(existing)+(arbitrary*Particle_j\_it\_(existing))$ (18)

Step 3.2: modernize particles by using the following equation

$Particle_j\_it\_(new)=arbitrary*Particle_j\_it\_(existing)$ (19)

Step 3.3: position of each particle modernized by using by following,;

$Particle_i\_position\_(new) = Particle_i\_position\_(existing) +(arbitrary*(Particle_j\_it\_(existing)*(global\_most\_excellent\_position-Particle_i\_position\_(existing))))$ (20)

Step 3.4: new position of each particles fitness value are calculated.

*most excellent_particle_it_(new) = most excellent_particle_it_(existing)+(arbitrary *most excellent_particle_it_(existing)))* (21)

Step 3.5 Maturation stage: Particles "it" values are modernized in arbitrary mode

$Particle_j\_it\_(new)=Particle_j\_it\_(existing)+(arbitrary*Particle_j\_it\_(existing))$ (22)

Compute the fitness values according to the new-fangled position of each particle and modernize the most excellent fitness of the particles.

Step 3.6 Rationalizing stage: particles are updated as below.

$Particle_j\_it\_(new)=Particle_j\_it\_(existing)+(arbitrary*(most\ excellent\_particle\_it\_(existing)/Particle_j\_it\_(existing)))$ (23)

$Particle_i\_position\_(new)=Particle_i\_position\_(existing) +(arbitrary*(Particle_j\_it\_(existing)*(global\_most\_excellent\_position-Particle_i\_position\_(existing))))$ (24)

Once again particle are modernize is done when the "it" value is equal or higher than specified limits, by following;

$Particle_j\_it\_(new)=Particle_j\_it\_(existing)+(arbitrary*(most\ excellent\_particle\_it\_(existing)/Particle_j\_it\_(existing)))$ (25)

Step 3.7 Balancing stage: Particles "it" values are modernized by below,

$Particle_j\_it\_(new)=arbitrary*Particle_j\_it\_(existing)$ (26)

Compute the fitness values according to the new-fangled position of each particle and modernize Particles "it" value, by following;

*most excellent_particle_it_(new)= most excellent_particle_it_(existing)+(arbitrary *most excellent_particle_it_(existing))* (27)

Step 4: The best value with respect to optimal solution is obtained within the loop.

Black hole algorithm

In Black Hole Algorithm (BHA) 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. Excellent candidate amongst all the candidates in iterations is chosen as a black hole and remaining candidates structured as the standard stars. Black hole formation is not capricious but it is form as genuine candidates of the created population. Towards the black hole, all the candidates are stimulated grounded on their present location with a random number. Production of population is capricious and in the exploration space candidates, stars are present [20]. Fitness value for the population is computed and the most excellent candidate in the population, which possess good fitness value, is picked to be the black hole and remaining form as the normal stars. The black hole has the ability to take in the stars that surround it.

Incorporation of stars by the black hole is given as,

$$Y_i(t+1)=Y_i(t)+random\times(Y_{BH}-Y_i(t))\ i=1,2,..,N \tag{28}$$

Event horizon radius of black hole algorithm is computed as,

$$R=\frac{f_{BH}}{\sum_{i=1}^{N} f_i} \tag{29}$$

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 (Yi) is given by,

$$Y_i=(star_i,\dots,star_N,\ blcakhole_d) \tag{30}$$

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

$$E_{ij}^d=\xi(t_o)\frac{C_{pi}(t)\times C_{aj}(t)\times(star_j(t)-star_i(t))}{(D_{ij}(t)+\varepsilon)^2\times(C_{pi}(t)+C_{aj}(t))}\times\left(\frac{t_o}{t-t_o}\right)^a \tag{31}$$

Complete force is randomly weighted by,

$$E_i^d(t)=\sum_{j=1\,J\neq i}^{N} random_i E_{ij}^d(t) \tag{32}$$

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

$$a_i^d(t)=\frac{E_i^d(t)}{C_{ii}(t)} \tag{33}$$

Position, velocity are calculated by,

$$v_i^d(t+1)=random_i\times v_i^d(t)+a_i^d(t) \tag{34}$$

$$star_i(t+1)=star_i(t)+v_i^d(t+1) \tag{35}$$

a. population of stars are initialized with capricious locations in the search space loop

b. objective function value for each star has been calculated

c. star which possess most excellent fitness value is chosen as black hole

d. Position of every star is modified by $Y_i(t+1)=Y_i(t)+random\times(Y_{BH}\_,Y_i(t))i=1,2,..,N$

e. When black hole, superior to a star location then exchange the locations

f. In event horizon when a star cross black hole, replace with a new star in capricious location in exploration space

g. If an end condition is met, egress the loop

h. Close of loop

1. Initialization

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.

2. Mutation and cross over is calculated by

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

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

3. Position, velocity are calculated by,

$$v_i^d(t+1)=random_i\times v_i^d(t)+a_i^d(t)$$

$$star_i(t+1)=star_i(t)+v_i^d(t+1)$$

4. Endurance criterion calculated by

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

5. Vector correction is done through

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

6. If maximum generation gmax is attained, then stop, or else, go to Step 2

Enhanced bat algorithm

Bat algorithm is mimicked from the actions of the Bat; mainly time delays are used for emission to reflection and employ it for navigation. To sense the distance and for other activities Echolocation used mainly. With velocity ϑ_i at position x_i with a set frequency f_{min}, changeable wavelength λ and loudness A_0 Bats fly capriciously to look for the prey. Wavelength can be attuned routinely and can control the rate of pulse emission r $\in$ [0; 1], depend on the proximity of the goal [14]. Loudness is assumed to be varying from a large (positive) A_0 minimum constant value A_{min}.

New-fangled solutions are produced by,

$$Q_i^{(t)}=Q_{min}+(Q_{max}-Q_{min})\cup(0,1) \tag{36}$$

$$v_i^{(t+1)}=v_i^t+(x_i^t-best)Q_i^{(t)} \tag{37}$$

$$x_i^{(t+1)}=x_i^{(t)}+v_i^{(t)} \tag{38}$$

For local search a capricious walk with direct exploitation is used to modernize the present most excellent solution by:

$$x^{(t)}=best+\epsilon A_i^{(t)}(2U(0,1)-1) \tag{39}$$

$\in$-scaling factor, $A_i^{(t)}$-loudness. Depending on the pulse rate ri and new-fangled solutions are accepted with some proximity local search will be commenced [14]. When bat finds a prey rate of pulse emission ri augments and loudness Ai diminished, which mathematically written by,

$$A_i^{(t+1)}=\alpha A_i^{(t)},\ r_i^{(t)}=r_i^{(0)}[1-\exp(-\gamma\in)] \tag{40}$$

In the projected Bat Algorithm with Combination of Numerous Schemes (BACS) many operators take part to decide about the convergence ability of the algorithm. The global convergence capability of the algorithm becomes weaker when the progress of operator increases and when the exploration operator augments, then the convergence accurateness will be inadequate. Consequently, in this paper, numerous schemes have been selected to solve the problem and it work as autonomous selection strategy. In the proposed algorithm different individuals prefer different strategy to modernize the position with reference to the quality of fitness.

Strategy "a"

Velocity and position are updated by,

$$x_{ik}(t+1) = x_{ik}(t) + v_{ik}(t+1) \quad (41)$$

$$v_{ik}(t+1) = v_{ik}(t) + \left(x_{ik}(t) - p_k(t)\right) \cdot f_i \quad (42)$$

Strategy "b"

Velocity and position are updated by,

$$x_{ik}(t+1) = x_{ik}(t) + v_{ik}(t+1) \quad (43)$$

$$v_{ik}(t+1) = v_{ik}(t) + \left(x_{ik}(t) - \omega_k(t)\right) \cdot f_i \quad (44)$$

Position of the worst individual is defined as "ω_k"

Strategy "c"

Position and velocity are updated by using the Levy flight as,

$$f_t^i = \left(\left(f_{max} - f_{min}\right) \frac{t}{n_t} + f_{min} \right) \beta \quad (45)$$

$$v_t^i = \left(\hat{x}_i - x^*\right) f_t^i \quad (46)$$

$$x_t^i = \hat{x}_i + usign\left[random(1) - \frac{1}{2} \right] \oplus Levy(\lambda) \quad (47)$$

Strategy "d"

Through Levy flight position and velocity are updated by,

$$x_i^{t+1} = x_i^t + Levy(\lambda) \otimes \left(x_i^t - x^*\right) \quad (48)$$

Strategy "e"

By using the Genetic algorithm position and velocity are updated by,

$$x_i(t+1) = Dx_i(t) + (1-D)x_i^*(t) \quad (49)$$

Strategy "f"

By using the particle swarm optimization algorithm position and velocity are updated by,

$$v_{ik}(t+1) = v_{ik}(t) + r_1\left(x_{ik}(t) - p_{gk}(t)\right)_i + r_1\left(x_{ik}(t) - p_{gk}(t)\right) \quad (50)$$

$$x_{ik}(t+1) = x_{ik}(t) + v_{ik}(t+1) \quad (51)$$

Strategy "g"

Based on inertial parameters local disturbance strategy defined as,

$$x_i(t+1) = x_t^*(t) + \omega r \quad (52)$$

$$\omega = \omega_{max} - \left(\omega_{max} - \omega_{min}\right) \cdot t / T_{max} \quad (53)$$

Strategy "h"

Local search strategy of flight to optimal position is defined by,

$$x_i(t+1) = x_t^*(t) + r \cdot \left(p_{gk}(t) - x_{ik}(t)\right) \quad (54)$$

Based on the value of probability the above strategies are selected. Consequently, the number of bat individuals preferring different strategies which vary from generation to generation. Every strategy alters the probability of it being selected with reference to the assessment results. Once the fitness value is superior, then the probability of the strategy will be attuned by,

$$P(n+1) = P(n) + (1-\lambda) \cdot P(n) \quad (55)$$

Or else it can be calculated as,

$$P(n+1) = \lambda \cdot P(n) \quad (56)$$

Start

Initialize the position, velocity, parameters, probability for each bat

While (end condition is met)

Capriciously engender the frequency for each bat by $Q_i^{(t)} = Q_{min} + \left(Q_{max} - Q_{min}\right) \cup (0,1)$

Calculate its fitness value;

Toggle number = 8

Scheme 1 (random<p1)

Modernize the velocity and position with strategy "a"

Scheme 2 (p1<random<p2)

Modernize the velocity and position with strategy "b"

Scheme 3 (p2<random<p3)

Modernize the velocity and position with strategy "c"

Scheme 4 (p3<random<p4)

Modernize the velocity and position with strategy "d"

Scheme 5 (p4<random<p5)

Modernize the velocity and position with strategy "e"

Scheme 6 (p5<random<p6)

Modernize the velocity and position with strategy "f"

Scheme 7 (p6<random<p7)

Modernize the velocity and position with strategy "g"

Scheme 8 (p7<random<p8)

Modernize the velocity and position with strategy "h"

Calculate its fitness value;

When the position is modernize then renew the loudness and emission rate;

Revise the probability table;

If pi<0; Pi = 0.001;

End

End

Grade the bats and accumulate the most excellent position;

End

Output the best position;

End

RESULTS

At first in standard IEEE 14 bus system the validity of the Projected Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) has been tested and comparison results are presented in Table 1 [21].

Then the proposed Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) has been tested, in IEEE 30 Bus system. Comparison results are presented in Table 2 [22].

Then IEEE 300 bus system [23] is used as test system to validate the

Table 1: Comparison results of Black Hole Algorithm (BHA) and Bat Algorithm with Combination of numerous Schemes (BACS).

Control variables	ABCO	IABCO	IGSO	CDO	BHA	BACS
V1	1.06	1.05	1.03	1.01	1.04	1
V2	1.03	1.05	1.01	1.04	1.01	1.03
V3	0.98	1.03	1.04	1.01	1.02	1.01
V6	1.05	1.05	1.02	1.05	1	1.02
V8	1	1.04	0.9	0.93	0.9	0.92
Q9	0.139	0.132	0.1	0.101	0.1	0.103
T56	0.979	0.96	0.9	0.903	0.902	0.904
T47	0.95	0.95	0.9	0.905	0.905	0.901
T49	1.014	1.007	1	1.001	1.003	1.002
Ploss (MW)	5.92892	5.50031	4.1326	4.132	4.1328	4.1319

Table 2: Power loss comparison.

Control variables	Control variables	Control variables	Control variables	Control variables	SARGA	IGSO	CDO	BHA	BACS
Reduction in PLoss (%)	0	8.4	7.4	6.6	8.3	19.54	17.2	20.28	25.6
Total PLoss (Mw)	17.55	16.07	16.25	16.38	16.09	14.12	14.53	13.99	13.057

Table 3: Comparison of Real Power Loss (RPL).

Parameter	Method EGA	Method EEA	Method CSA	IGSO	CDO	BHA	BACS
PLOSS (MW)	646.2998	650.6027	635.8942	619.5364	618.101	615.7862	611.0429

performance of the Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS). Table 3 shows the comparison of real power loss obtained after optimization [24,25].

DISCUSSION AND CONCLUSION

Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) successfully solved the optimal reactive power problem. Glow worm Swarm Optimization Algorithm incorporated with the parallel hybrid mutation which unites the uniform distribution mutation with the Gaussian distribution mutation. In proposed (IGSO) algorithm dynamic moving step length is implemented to each individual. When the position unchanged in any generation then Normal distribution variation to the glow worm is applied. Projected CDO algorithm developed from the Piaget's Theory on Cognitive Development, which has maturation, social interaction, balancing-throughout all the phases are efficiently tuned the algorithm to improve the exploration and exploitation. In BHA Evolution of the population is through push the candidate in the itinerary of the most exceptional candidate in iterations and black hole which exchange with those 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. In BACS numerous schemes have been selected to solve the problem and it work as autonomous selection strategy. In the proposed algorithm different individuals prefer different strategy to modernize the position with reference to the quality of fitness. Proposed Improved Glow worm Swarm Optimization (IGSO) algorithm, Cognitive Development Optimization (CDO) algorithm, Black Hole Algorithm (BHA) and Bat Algorithm with Combination of Numerous Schemes (BACS) has been tested in standard IEEE 14, 30,300 bus test system and simulation results show the projected algorithm reduced the real power loss considerably.

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