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FACTUAL POWER LOSS LESSENING BY ENHANCED SYNTHETIC BIOME OPTIMIZATION AND GREEN ALGAE ALGORITHMS

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Abstract

In this paper Enhanced Synthetic Biome Optimization (ESBO) and Green Algae algorithm (GAA) is designed to abridge the power loss. Synthetic Biome Optimization (SBO) algorithm is a nature-inspired optimization algorithm, stimulated by the stream of energy in a biome on the world. The biome can be enunciated as a cluster of existing entities living in a certain province and the biome outlines the associations among them. The deprived entity (creator) is rationalized by the upper and low borders of exploration space and the pre-eminent entity (putrefaction). Levy flight applied to augment the exploration and imitate the food probing process of many faunae. In order to augment the convergence characteristics of the SBO algorithm, sine-cosine functions has been incorporated in the technique. This augmentation will stimulate divergent solutions and modifies in the direction of the distinguished prospective solution in ESBO. Proposed GAA approach imitates growing, reproduction deeds of green algae in sunlight. Green algae live in the shape of algal colonies which consist of algal cells. When green algae in least amount of sunlight it will be small size, energy and particularly starvation level will be high, but it will attempt to acclimatize by using adaptation probability in the ambiance where it positioned. Enhanced Synthetic Biome Optimization and GAA appraised in IEEE 57 and 300 bus systems. Assessment with other techniques has been done. Projected ESBO and GAA approaches abridged the power loss meritoriously

Keywords

Optimization, Transmission loss, Green Algae, Synthetic Biome, algorithm

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Introduction. Lessening of real power loss is the foremost aim of this paper. Year by year various techniques has been sequentially applied to solve the problem. Sundry types of conventional methods [1–6] and evolutionary algorithms [7–13] have been applied to solve the problem. In this paper Enhanced Synthetic Biome Optimization (ESBO) and Green Algae Algorithm (GAA) are projected to solve the power loss lessening problem. Synthetic Biome Optimization (SBO) algorithm is inspired by the stream of energy in a biome on the world. The biome can be expressed as a cluster of prevailing entities living in a certain section and the biome delineates the connections among them. Synthetic Biome Optimization algorithm emulates three elite deeds of prevailing creatures, which encompasses three stages, creation, ingesting, and putrefaction. In the primary phase creators won't obtain energy from other creatures, wherever extreme creators are florae. In the following segment customers are faunae are indicated as clients, everywhere they cannot engender their own foodstuff. These faunae attain nutrients from a creator or auxiliary customers. Concluding stage is putrefaction, which feeds on in the same way creators (defunct florae) or customers (discarded (waste) from prevailing creatures). These three stages are correlating with one another which encompass a nutrients categorization. In creation phase, a fresh entity is capriciously created between a single arbitrarily originated in the exploration space and the distinguished entity. The ingestion permits the technique to streamline the solutions of entities with orientation to either one of the solution presented by the way out of the capriciously designated entity with established energy level, the creation procedure or, together. Putrefaction authorizes SBO approach to streamline the solutions of entities grounded on the distinguished solution in the population through putrefaction factors H and along with weight parameters o and p. The putrefaction advances the exploitation of the SBO technique. In order to enrich the convergence features of the SBO algorithm, sine-cosine functions has been combined in the method. This enrichment will stimulate disparate solutions and amends in the direction of the outstanding potential solution in ESBO. GAA approach imitates growing, reproduction deeds of green algae in sunlight. Where sufficient sunlight is there green algae swim in the liquid in the direction of the sunlight for photosynthesis. Green algae live in the shape of algal colonies which consist of algal cells. In the period of the exploration for optimal light condition algal colony will find the most excellent sunlight for the action of photosynthesis which reproduces itself and it possess the features of biggest size, utmost energy with least amount of starvation level. Green algal colony which possesses gigantic dimension will emulate capriciously selected algal cell in the position of vanishing algal cell of slightest colony and replication of cells be illustrated as evolution. Green Algae Algorithm possesses “3” vital conceptions: 1) Evolution (progression),

2) Helical movement (progress), 3) Adaptation (alteration). Proposed ESBO and GAA appraised in IEEE 57 and 300 bus systems. Lessening of real power loss is accomplished and proportion of actual power loss lessening is enriched.

Problem formulation. Power loss objective function is defined as (VD is voltage deviation):

$$F = P_L = \sum_{k \in N_{br}} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij} \right); \; F = P_L + \omega_v VD,$$

$$VD = \sum_{i=1}^{N_{pq}} \left| V_i - 1.0 \right|.$$

Parity constraint is defined as follows: $P_G = P_D + P_L$. Disparity constraint is described as

$$P_{gslack}^{\min} \le P_{gslack} \le P_{gslack}^{\max};$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \; i \in N_g;$$

$$V_i^{\min} \le V_i \le V_i^{\max}, \; i \in N_b;$$

$$T_i^{\min} \le T_i \le T_i^{\max}, \; i \in N_T;$$

$$Q_C^{\min} \le Q_C \le Q_C^{\max}, \; i \in N_C.$$

Enhanced Synthetic Biome Optimization. Synthetic Biome Optimization algorithm is a nature-inspired optimization algorithm, enthused by the stream of energy in a biome on the globe. The biome can be articulated as a cluster of existing entities living in a definite region and the biome defines the relationships among them. Synthetic Biome Optimization algorithm imitates three exclusive deeds of existing creatures, which comprises three stages, creation, ingesting, and putrefaction. In the initial stage creators won't acquire energy from other creatures, wherever utmost creators are florae. In the subsequent segment customers are faunae are signified as clients, everywhere they cannot create their own foodstuff. These faunae acquire nutrients from a creator or supplementary customers. Final stage is putrefaction, which feeds on equally creators (deceased florae) or customers (left-over (waste) from existing creatures). These three stages are interrelating with one another comprise a nutrients sequence.

The SBO algorithm exploits these three phases. Preliminary stage is primarily to progress the stability between exploitation and exploration. The subsequent phase is used to expand the exploration of the SBO procedure. Final phase will augment the exploitation of the SBO process. In SBO approach, there is only one putrefaction entity and one creator. The remaining entities are measured as customers.

Creation. In this stage, a new-fangled entity is arbitrarily created between a single arbitrarily originated in the exploration space (y_{random}) and the pre-eminent entity (y_n). The poorest entity (creator) is rationalized by the upper and low borders of exploration space and the pre-eminent entity (putrefaction). This rationalized entity guides other entities to explore the dissimilar areas. This deed contributes for balancing the exploration and exploitation. The mathematical model for this phase can be expressed as follows:

$$y_1(t+1) = (1-g)\, y_n(t) + g y_{random}(t), \tag{1}$$

$$g = \left(1 - \frac{t}{maximum\ iteration}\right) d_1,\ d_1 \in [0,1],$$

$$y_{random} = d\left(Upper\, Bound\,(UB) - Lower\, Bound\,(LB)\right) + LB,\ d \in [0,1],$$

where g is linear weight coefficient; n is population number.

Ingesting. The ingestion allows the procedure to modernize the solutions of entities with reference to either one of the solution presented by the way out of the arbitrarily selected entity with developed energy level, the creation procedure or, together. This will improve the exploration of the procedure. Levy flight [14–16] applied to augment the exploration and imitate the food probing process of many faunae. Levy flight is defined as below:

$$I = \frac{1}{2}\frac{v_1}{|v_2|},\ v_1 \widetilde{ND}(0,1),\ v_2 \widetilde{ND}(0,1),$$

where $\widetilde{ND}(0,1)$ symbolize the normal distribution.

This ingestion feature will benefit each of the customers to get foodstuff by means of diverse hunting stratagems. Three categories of customers are: first is Herbivore which consumes only creators and customers, then Carnivore, consume the customers which possess high energy and Omnivore which consumes other customers which has greater energy or creators (both).

Based on an arbitrary selection, the customer can be categorized as one of the "3" stated types. The scientific models for the customer, when it is designated as an herbivore kind, Carnivore which consumes the customers which possess high energy and Omnivore which consumes other customers which has greater energy or creators (both) are denoted as

$$y_i(t+1) = y_i(t) + I\left(y_i(t) - y_1(t)\right),\ i \in (2, 3, \ldots, n); \tag{2}$$

$$y_i(t+1) = y_i(t) + I(y_i(t) - y_j(t)),\ i \in (3, 4 \ldots, n), \\ \text{then } j = \text{random } i([2i-1]); \tag{3}$$

$$y_i(t+1) = y_i(t) + I(R_2(y_i(t) - y_j(t))) + (1 - R_2)(y_i(t) - y_j(t)), \\ i = 3, 4, \ldots, n, \text{ then } j = \text{random } i([2i-1]). \tag{4}$$

Putrefaction empowers SBO to modernize the solutions of entities grounded on the pre-eminent solution in the population through "3" putrefaction factors, which comprise feature H along with weight parameters o and p. The putrefaction progresses the exploitation of the SBO procedure. The location of the i-th entity y_i in the population can be rationalised based on the putrefaction factor y_n and using a putrefaction aspect feature H along with weight parameters o and p as follows:

$$y_i(t+1) = y_n(t) + H(oy_n(t) - py_i(t)),\ i = 1, 2, 3, \ldots, n, \tag{5}$$

$$H = 3u,\ u\widetilde{ND}(0,1), \tag{6}$$

$$o = R_3\text{random } i([12]) - 1, \tag{7}$$

$$p = 2R_3 - 1. \tag{8}$$

SBO algorithm

a. Start
b. Define the parameters
c. Engender the population of biome system
d. Current iteration = 1
e. Compute the fitness value for each solution
f. Modernize the solution
g. Formula (1)
h. Is random < 1/3?
h. If yes, modernize the solution
i. Formula (2)
j. Otherwise, check 1/3 = random = 2/3
k. If yes, then modernize the solution
l. Formula (3)
m. Or else update the solution by using the equation (4)
n. Compute the fitness value for all type of solutions
o. Each entity position is updated by following equations (5)–(8)

p. Assessment of new-fangled solutions, if better than the preceding solution then it will be replaced by new one

q. Convergence criterion is checked
r. If yes end the procedure
s. Or else go to step e
t. End

In order to enhance the convergence characteristics of the SBO algorithm, sine-cosine functions [14–16] has been integrated in the procedure. This enhancement will engender dissimilar solutions and alters in the direction of the pre-eminent potential solution in ESBO:

$$R_1 = 2 - current\ \ iteration\left(\frac{2}{maximum\ \ iteration}\right),\ R_1 \in (0,1); \tag{9}$$

$$R_3 = 2\pi\ random(0,1),\ R_3 \in (0,1); \tag{10}$$

$$y_i(t+1) = \begin{Bmatrix} y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_1(t)\big) R_4 < 0.50,\ i \in [2, 3, \ldots, n] \\ y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_1(t)\big) R_4 > 0.50,\ i \in [2, 3, \ldots, n] \end{Bmatrix}; \tag{11}$$

$$y_i(t+1) = \begin{Bmatrix} y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_j(t)\big) R_4 < 0.50,\ i \in [3, 4, \ldots, n] \\ y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_j(t)\big) R_4 > 0.50,\ i \in [3, 4, \ldots, n] \\ j = random\ \ i([2i-1]) \end{Bmatrix}; \tag{12}$$

$$y_i(t+1) = \begin{Bmatrix} y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_j(t)\big) + \\ +(1-R_2)\big(y_i(t) - y_j(t)\big) R_4 < 0.50,\ i \in [3, 4, \ldots, n] \\ y_i(t) + R_1 \sin R_3 HI\big(y_i(t) - y_j(t)\big) + \\ +\ (1-R_2)\big(y_i(t) - y_j(t)\big) R_4 > 0.50,\ i \in [3, 4, \ldots, n] \\ j = random\ \ i([2i-1]) \end{Bmatrix}.$$

ESBO

a. Start
b. Define the parameters
c. Engender the population of biome system
d. Current iteration = 1
e. Compute the fitness value for each solution
f. Modernize the solution
g. Formula (1)
h. Is random < 1/3?

i. If yes, modernize the solution (9)–(11)
j. Otherwise, check 1/3 = random = 2/3
k. If yes, then modernize the solution (9), (10), (12)
l. Or else update the solution by using the following equation (9), (10), (12)
m. Compute the fitness value for all type of solutions
n. Each entity position is updated by equations (5)–(8)
o. Assessment of new-fangled solutions, if better than the preceding solution then it will be replaced by new one
p. Convergence criterion is checked
q. If yes end the procedure
r. Or else go to step e
s. End

Green Algae Algorithm. Green Algae Algorithm imitates growing, reproduction deeds of green algae in sunlight. Where sufficient sunlight is there green algae swim in the liquid in the direction of the sunlight for photosynthesis. Green algae live in the shape of algal colonies which consist of algal cells. In the period of the exploration for optimal light condition algal colony will find the most excellent sunlight for the action of photosynthesis which reproduces itself and it possess the features of biggest size, utmost energy with least amount of starvation level. When green algae in least amount of sunlight it will be small size, energy and particularly starvation level will be high, but it will try to adapt itself in the environment with an adaptation probability when it is flourishing then that colony will be most excellent colony otherwise it will die. Green algal colony which possesses the big size will imitate the arbitrarily selected algal cell. Green Algae Algorithm possesses three basic conceptions: 1) Evolution (progression), 2) Helical movement (progress), 3) Adaptation (alteration). Let $\left(y_i^{\max}, y_i^{\min}\right)$ indicates algal cells explore range $\left(y_i^j,\ i=1,2,3,\ldots,N,\ j=1,2,3,\ldots,N+1\right)$ in artificial search space and calculate the objective function $\left(F_j\left(y_i^j\right),\ j=1,2,\ldots,N+1\right)$:

$$D_j = D_j + \mu_j D_j,\ j=1,2,\ldots,N+1, \tag{13}$$

where $\mu_j,\ j=1,2,\ldots,N+1,$ is Monod function for algal growth. It is given by

$$\mu_j = \frac{2G_j}{D_j + 2G_j},\ j=1,2,\ldots,N+1. \tag{14}$$

Here $G_j,\ j=1,2,\ldots,N+1,$ is the fitness function,

$$G_j = \begin{cases} \dfrac{F_j - F_{\min}}{F_{\max} - F_{\min}}, & Max; \\ \dfrac{F_{\max} - F_j}{F_{\max} - F_{\min}}, & Min, \end{cases} \quad (15)$$

E_j of each algal colony is computed by

$$E_j = \frac{B_j - B_{\min}}{B_{\max} - B_{\min}}, \ j = 1, 2, \ldots, N+1, \quad (16)$$

$$B_j = D_j^2, \ j = 1, 2, \ldots, N+1.$$

In helical pattern algal colonies spin in liquid. In the period of helical movement when algal colony discover a superior solution than the starvation then that colony leftover as unaffected or else hunger level of colony is augmented by one:

$$y_m^j = y_m^j + \left(y_m^i - y_m^j \right) \left(\Delta - \tau_j \right) \rho; \quad (17)$$

$$y_k^j = y_k^j + \left(y_k^i - y_k^j \right) \left(\Delta - \tau_j \right) \cos \alpha; \quad (18)$$

$$y_l^j = y_l^j + \left(y_l^i - y_l^j \right) \left(\Delta - \tau_j \right) \sin \beta, \quad (19)$$

$\alpha, \beta \in [0, 2\pi]$; $\rho \in [-1, 1]$; (m, k, l) is three dissimilar arbitrarily selected j-th algal colony;

$$\tau_j = 2\pi \left(\sqrt[3]{\frac{3D_j}{4\pi}} \right), \ j = 1, 2, \ldots, N+1.$$

In adaptation segment (probability) A_p progress towards most excellent position is given by

$$y_i^D = y_i^D + \left(y_i^b - y_i^D \right) random(0, 1), \ i = 1, 2, \ldots, N.$$

GAA

a. Initialize the parameters
b. Population of algal colonies are initiated
c. Preliminary size of the colony is $D_j = 1, \ j = 1, 2, \ldots, N+1$
d. Preliminary hunger level is $H_j = 1, \ j = 1, 2, \ldots, N+1$
e. $t = 0$
f. $t = t + 1$

g. Computation of objective function

h. Consign, dimension and power of every algal colony is computed by (13)–(16), (20) and reduce the energy by $E_j = E_j - \in/2$

i. $j = 0$

j. $j = j + 1$

k. When $E_j > 0$ helical movement done by (17)–(20)

l. When there is no enhancement then augment the hungry level by $H_j = H_j + 1$

m. When $j < N + 1$, then go to step j or else go to next step

n. Size of the algal colony is modernized by (13)–(15)

o. When $random(0,1) > A_p$, then adaptation is done by (21)

p. When $t < M$, then go to step f or else stop the process

Simulation study. Performance validation of SBO, ESBO and GAA corroborated in IEEE 57 and 300 bus systems [17]. Table 1 and 2 show the restrictions of variables, table 3 shows the appraisal results. Figure shows the assessment of actual power loss and diminution in proportion value of loss. Table 4 shows the convergence characteristics of SBO, ESBO and GAA. Performance of the proposed algorithms compared with Modified Particle Swarm Optimization (MPSO) [18], Particle Swarm Optimization (PSO) [19], Canonical Genetic Algorithm (CGA) [20], Adaptive Genetic Algorithm (AGA) [20], Enhanced Genetic Algorithm (EGA) [22], Enhanced Faster Evolutionary Algorithm (EEA) [22] and Cuckoo Search optimization Algorithm (CSA) [21]. Power loss has been abridged effectively by SBO, ESBO and GAA.

Table 1

Variable limits (IEEE 57 bus system)

Item	Value, PU	
	min	max
VG	0.9500000	1.10000
TT	0.9000000	1.10000
VAR	0.0000000	0.20000

Table 2

Constrains limits (IEEE 57 bus system)

Bus	1	2	3	6	8	9	12
Q_{min} / Q_{max}, PU	−140/200	−17/50	−10/60	−8/25	−140/200	−3/9	−150/155

Table 3

Appraisal of values with other algorithms (IEEE 57 bus system)

Item	Value of base case [18]	MPSO [18]	PSO [19]	CGA [20]	AGA [20]	SBO	ESBO	GAA
VG-01	1.0400	1.0930	1.0830	0.9680	1.0270	1.016	1.015	1.014
VG-02	1.0100	1.0860	1.0710	1.0490	1.0110	1.019	1.018	1.017
VG-03	0.9850	1.0560	1.0550	1.0560	1.0330	1.024	1.022	1.020
VG-06	0.9800	1.0380	1.0360	0.9870	1.0010	1.016	1.015	1.013
VG-08	1.0050	1.0660	1.0590	1.0220	1.0510	1.028	1.026	1.025
VG-09	0.9800	1.0540	1.0480	0.9910	1.0510	1.025	1.023	1.020
VG-12	1.0150	1.0540	1.0460	1.0040	1.0570	1.029	1.029	1.029
TT-19	0.9700	0.9750	0.9870	0.9200	1.0300	0.909	0.909	0.909
TT-20	0.9780	0.9820	0.9830	0.9200	1.0200	0.904	0.905	0.906
TT-31	1.0430	0.9750	0.9810	0.9700	1.0600	0.913	0.914	0.912
TT-35	1.0000	1.0250	1.0030	NR*	NR*	1.001	1.001	1.001
TT-36	1.0000	1.0020	0.9850	NR*	NR*	1.014	1.014	1.014
TT-37	1.0430	1.0070	1.0090	0.9000	0.9900	1.010	1.010	1.010
TT-41	0.9670	0.9940	1.0070	0.9100	1.1000	0.909	0.909	0.909
TT-46	0.9750	1.0130	1.0180	1.1000	0.9800	1.019	1.019	1.018
TT-54	0.9550	0.9880	0.9860	0.9400	1.0100	0.929	0.928	0.927
TT-58	0.9550	0.9790	0.9920	0.9500	1.0800	0.924	0.922	0.920
TT-59	0.9000	0.9830	0.9900	1.0300	0.9400	0.937	0.936	0.935
TT-65	0.9300	1.0150	0.9970	1.0900	0.9500	1.044	1.044	1.043
TT-66	0.8950	0.9750	0.9840	0.9000	1.0500	0.904	0.904	0.904
TT-71	0.9580	1.0200	0.9900	0.9000	0.9500	1.018	1.016	1.015

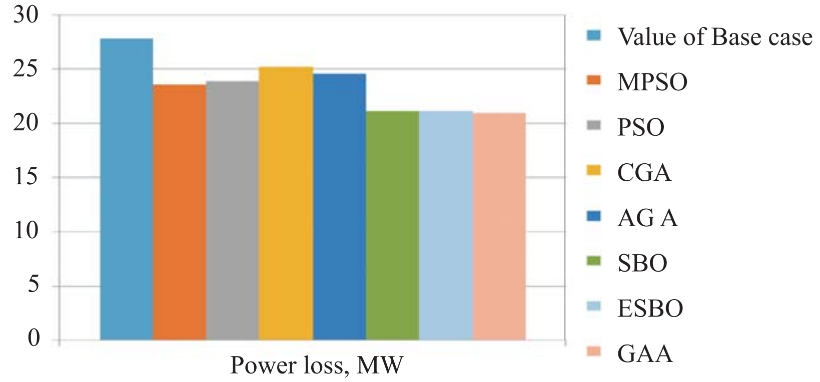
End of the Table 3

Item	Value of base case [18]	MPSO [18]	PSO [19]	CGA [20]	AGA [20]	SBO	ESBO	GAA
TT-73	0.9580	1.0010	0.9880	1.0000	1.0100	1.015	1.014	1.013
TT-76	0.9800	0.9790	0.9800	0.9600	0.9400	0.924	0.923	0.921
TT-80	0.9400	1.0020	1.0170	1.0000	1.0000	1.014	1.012	1.010
QC-18	0.1000	0.1790	0.1310	0.0840	0.0160	0.129	0.129	0.129
QC-25	0.0590	0.1760	0.1440	0.0080	0.0150	0.133	0.131	0.130
QC-53	0.0630	0.1410	0.1620	0.0530	0.0380	0.100	0.100	0.100
PG, MW	1278.60	1274.40	1274.80	1276.0	1275.0	1272.14	1272.11	1272.09
QC (MVAR)	321.080	272.270	276.580	309.10	304.40	272.18	272.17	272.14
Proportion of power loss lessening, %	0	15.40	14.10	9.20	11.60	24.03	24.07	24.72
Power loss, MW	27.80	23.510	23.860	25.240	24.560	21.119	21.108	20.926

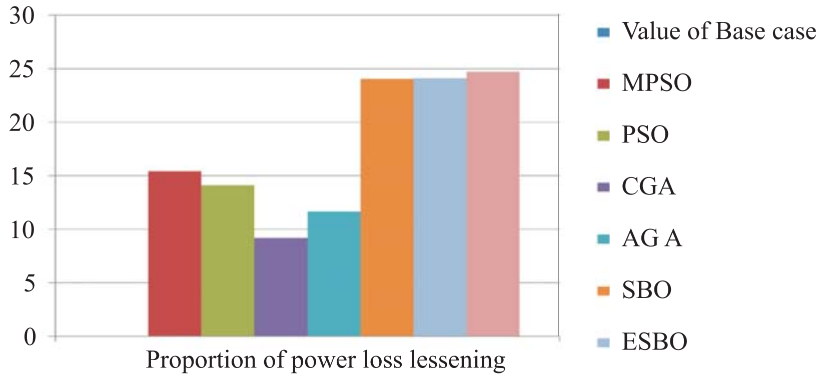
NR* — not reported.

Assessment of loss (IEEE 300 bus system)

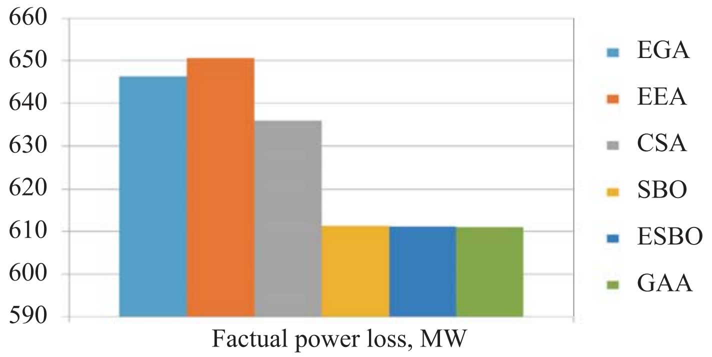
	EGA [22]	EEA [22]	CSA [21]	SBO	ESBO	GAA
Factual power loss, MW	646.299800	650.602700	635.89420	611.3714	611.1978	610.9929



a



b



c

Power loss appraisal (*a*), actual power loss lessening in percentage (*b*), assessment of factual power loss (*c*)

Table 4

Convergence characteristics of ESBO and GAA

Algorithm	Factual power loss, MW	Time, s	Number of iterations	Factual power loss, MW	Time, s	Number of iterations
IEEE 57 bus system				*IEEE 300 bus system*		
SBO	21.119	16.99	24	611.3714	49	69
ESBO	21.108	14.76	20	611.1978	47	64
GAA	20.926	14.01	18	610.9929	40	59

Conclusion. Proposed ESBO and GAA efficaciously abridged the factual power loss. Synthetic Biome Optimization algorithm imitates three exclusive deeds of existing creatures, which comprises three stages, creation, ingesting, and putrefaction. Preliminary stage is primarily to progress the stability between exploitation and exploration. The subsequent phase is used to expand the exploration of the SBO procedure. Final phase will augment the exploitation of the SBO process. In SBO approach, there is only one putrefaction entity and one creator. The remaining entities are measured as customers. The scientific model for the customer, when it is designated as an Herbivore kind, Carnivore which consumes the customers has high energy and Omnivore which consumes other customers which has greater energy or creators. Putrefaction empowers SBO to modernize the solutions of entities grounded on the pre-eminent solution in the population through putrefaction factors, which comprise feature H along with weight parameters o and p. The putrefaction progresses the exploitation of the SBO procedure. In order to enrich the convergence features of the SBO algorithm, sine-cosine functions has been combined in the method. This enrichment will stimulate disparate solutions and amends in the direction of the outstanding potential solution in ESBO. In GAA green algal colony which possesses the big size will replicate the capriciously picked algal cell. In the period of the exploration for optimal light condition algae colony will find the most excellent sunlight for the action of photosynthesis which reproduces itself and it possess the features of biggest size, utmost energy with least amount of starvation level. Proposed ESBO and GAA have been authenticated in IEEE 57 and 300 bus systems. Factual power loss lessening achieved competently. Proportion of reduction of actual power loss is augmented.

REFERENCES

[1] Davoodi E., Babaei E., Mohammadi-Ivatloo B., et al. A novel fast semidefinite programming-based approach for optimal reactive power dispatch. *IEEE Trans. Ind. Informat.*, 2020, vol. 16, iss. 1, pp. 288–298. DOI: https://doi.org/10.1109/TII.2019.2918143

[2] Zhang C., Chen H., Liang Z., et al. Reactive power optimization under interval uncertainty by the linear approximation method and its modified method. *IEEE Trans. Smart Grid*, 2018, vol. 9, iss. 5, pp. 4587–4600.
DOI: https://doi.org/10.1109/TSG.2017.2664816

[3] Bjelogrlic M.R., Calovic M.S., Ristanovic P., et al. Application of Newton's optimal power flow in voltage/reactive power control. *IEEE Trans. Power Syst.*, 1990, vol. 5, iss. 4, pp. 1447–1454. DOI: https://doi.org/10.1109/59.99399

[4] Xie J., Liang C., Xiao Y. Reactive power optimization for distribution network based on distributed random gradient-free algorithm. Energies, 2018, vol. 11, iss. 3, art. 534. DOI: https://doi.org/10.3390/en11030534

[5] Chen J.-S. Two classes of merit functions for the second-order cone complementarity problem. *Math. Meth. Oper. Res.*, 2006, vol. 64, no. 3, pp. 495–519.
DOI: https://doi.org/10.1007/s00186-006-0098-9

[6] Duong T.L., Duong M.Q., Phan V.-D., et al. Optimal reactive power flow for large-scale power systems using an effective Metaheuristic algorithm. *J. Electr. Comput. Eng.*, 2020, vol. 20. DOI: https://doi.org/10.1155/2020/6382507

[7] Tran H.V., Pham T.V., Pham L.H., et al. Finding optimal reactive power dispatch solutions by using a novel improved stochastic fractal search optimization algorithm. *TELKOMNIKA*, 2019, vol. 17, no. 5, pp. 2517–2526.
DOI: http://dx.doi.org/10.12928/telkomnika.v17i5.10767

[8] Packiasudha M., Suja S., Jerome J. A new Cumulative Gravitational Search algorithm for optimal allocation of FACT device to minimize system loss in deregulated electrical power environment. *Int. J. Electr. Power Energy Syst.*, 2017, vol. 84, pp. 34–46. DOI: https://doi.org/10.1016/j.ijepes.2016.04.049

[9] Naderi E., Narimani H., Fathi M., et al. A novel fuzzy adaptive configuration of particle swarm optimization to solve large-scale optimal reactive power dispatch. *Appl. Soft Comput.*, 2017, vol. 53, pp. 441–456. DOI: https://doi.org/10.1016/j.asoc.2017.01.012

[10] Vishnu M., Sunil K.T.K. An improved solution for reactive power dispatch problem using diversity-enhanced particle swarm optimization. *Energies*, 2020, vol. 13, art. 2862. DOI: https://doi.org/10.3390/en13112862

[11] Muthukumaran E., Kalyani S. Development of smart controller for demand side management in smart grid using reactive power optimization. *Soft Comput.*, 2021, vol. 25, no. 2, pp. 1581–1594. DOI: https://doi.org/10.1007/s00500-020-05246-3

[12] Ravisekar R., Srinivasan K. Optimal reactive power dispatch with series and shunt facts devices using sine cosine algorithm. *IJARET*, 2020, vol. 11, iss. 1, pp. 90–109.
DOI: https://doi.org/10.34218/ijaret.11.1.2020.012

[13] Medani K.B.O., Sayah S., Bekrar A. Whale optimization algorithm based optimal reactive power dispatch: a case study of the Algerian power system. *Electr. Power Syst. Res.*, 2018, vol. 163-B, pp. 696–705. DOI: https://doi.org/10.1016/j.epsr.2017.09.001

[14] Maleki A., Rosen M.A. Design of a cost-effective on-grid hybrid wind-hydrogen based CHP system using a modified heuristic approach. *Int. J. Hydrogen Energy*, 2017, vol. 42, iss. 25, pp. 15973–15989. DOI: https://doi.org/10.1016/j.ijhydene.2017.01.169

[15] Zhang W., Maleki A., Rosen M.A., et al. Sizing a stand-alone solar-wind-hydrogen energy system using weather forecasting and a hybrid search optimization algorithm. *Energy Convers. Manag.*, 2019, vol. 180, pp. 609–621.
DOI: https://doi.org/10.1016/j.enconman.2018.08.102

[16] Hatata A., Osman G., Aladl M. An optimization method for sizing a solar/wind/battery hybrid power system based on the artificial immune system. *Sustain. Energy Technol. Asses.*, 2018, vol. 27, pp. 83–93. DOI: https://doi.org/10.1016/j.seta.2018.03.002

[17] IEEE Data Port. IEEE-test systems.
Available at: https://ieee-dataport.org/keywords/ieee-test-systems
(accessed: 27.04.2022).

[18] Hussain A.N., Abdullah A.A., Neda O.M. Modified particle swarm optimization for solution of reactive power dispatch. *Res. J. Appl. Sci. Eng. Technol.*, 2018, vol. 15, no. 8, pp. 316–327. DOI: https://doi.org/10.19026/rjaset.15.5917

[19] Subbaraj P., Rajnarayan P.N. Optimal reactive power dispatch using self-adaptive real coded Genetic algorithm. *Electr. Power Syst. Res.*, 2009, vol. 79, iss. 2, pp. 374–381. DOI: https://doi.org/10.1016/j.epsr.2008.07.008

[20] Pandya S., Roy R. Particle swarm optimization based optimal reactive power dispatch. *Proc. IEEE ICECCT*, 2015. DOI: https://doi.org/10.1109/ICECCT.2015.7225981

[21] Reddy S.S. Optimal reactive power scheduling using Cuckoo Search algorithm. *IJECE*, 2017, vol. 7, no. 5, pp. 2349–2356.
DOI: http://doi.org/10.11591/ijece.v7i5.pp2349-2356

[22] Reddy S.S., Bijwe P.R., Abhyankar A.R. Faster evolutionary algorithm based optimal power flow using incremental variables. *Int. J. Electr. Power Energy Syst.*, 2014, vol. 54, pp. 198–210. DOI: https://doi.org/10.1016/j.ijepes.2013.07.019

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