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REAL POWER LOSS REDUCTION BY ENHANCED RUSSIAN HALIAEETUS PELAGICUS OPTIMIZATION ALGORITHM

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Abstract

In this paper Enhanced Russian Haliaeetus pelagicus Optimization Algorithm is applied for solving the Power loss lessening problem. Russian Haliaeetus pelagicus Optimization Algorithm is modeled based on the natural deeds of Russian Haliaeetus pelagicus. A spiral trajectory for exploration and a straight-line lane for assails done by Russian Haliaeetus pelagicus for hunting. It shows proclivity to sail in preliminary phase of hunting and efficiently changeover to further proclivity to assail in the concluding phases. Russian Haliaeetus pelagicus conserve proclivity for both sail and assail in each instant of the voyage. Sail vector is computed based on the assail vector. Sail vector is a tangent to the loop and vertical to the assail vector. The sail can be linear pace of Russian Haliaeetus pelagicus in comparison the prey. The sail vector in n-dimensions is situated within the tangent plane in loop in order compute the sail vector. In Enhanced Russian Haliaeetus pelagicus Optimization Algorithm exterior archive, prey precedence condition, and picking of prey are added through multi-objective mode. The fundamental plan is to keep capable solutions in an exterior archive and modernize when procedure continues. Exploration agents are moved in the direction of the stored entities. If the new-fangled solution is conquered by one or more of the present archives' entities, then the new-fangled solution is removed. If the new-fangled solution is not ruled over the present entities of the stored one and the records are not occupied, basically append the new-fangled position to the store. Prudence of the Enhanced Russian Haliaeetus pelagicus Optimization Algorithm is corroborated in IEEE 30 bus system (with and devoid of L-index). True power loss lessening is reached. Ratio of true power loss lessening is augmented

Keywords

Optimal reactive power, transmission loss, Russian Haliaeetus pelagicus

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Introduction. In power system diminishing of true power loss is an important feature. Abundant methods [1–6] and evolutionary approaches [7–16] are applied for solving power loss lessening problem. Carpentier [1] has done the work on "Contribution à l'étude du dispatching économique". Dommel et al. [2] did research on optimal power flow solutions. Takapoui et al. [3] did work on a simple effective heuristic for embedded mixed-integer quadratic programming. Abaci et al. [4] solved the optimal reactive-power dispatch using differential search algorithm. Pulluri et al. [5] worked on an enhanced self-adaptive differential evolution-based solution methodology for multi-objective optimal power flow. Heidari et al. [6] used Gaussian barebones water cycle algorithm for optimization Every Russian Haliaeetus pelagicus arbitrarily choose al reactive power dispatch in electrical power systems. Keerio et al. [7] solved Multi-Objective Optimal Reactive Power Dispatch Considering Probabilistic Load Demand Along with Wind and Solar Power Integration. Roy et al. [8] solved the Optimal Reactive Power Dispatch for Voltage Security using JAYA Algorithm. Mugemanyi et al. [9] solved the Optimal Reactive Power Dispatch Using Chaotic Bat Algorithm. Sahli et al. [10] solved Hybrid PSO-tabu search for the optimal reactive power dispatch problem. Mouassa et al. [11] used Ant lion optimizer for solving optimal reactive power dispatch problem in power systems. Mandal et al. [12] solved Optimal reactive power dispatch using quasi-oppositional teaching learning-based optimization. Khazali et al. [13] solved the Optimal reactive power dispatch based on harmony search algorithm. Tran et al. [14] did Finding optimal reactive power dispatch solutions by using a novel improved stochastic fractal search optimization algorithm. Polprasert et al. [15] solved the optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization. Thanh Long Duong et al. [16] solved Optimal Reactive Power Flow for Large-Scale Power Systems Using an Effective Metaheuristic Algorithm. On the other hand many procedures are unsuccessful to touch the global optimal solution. In this paper Enhanced Russian Haliaeetus pelagicus Optimization Algorithm (ERHOA) is applied for solving the power loss lessening problem. Russian Haliaeetus pelagicus Optimization Algorithm (RHOA) is designed based on the natural actions of Russian Haliaeetus pelagicus. A helix gesticulation will be performed during hunting. Russian Haliaeetus pelagicus should select a prey to carry out the sail and assail function in all iterations. Prey is scientifically modelled based on the most excellent solutions found by the group of Russian Haliaeetus pelagicus and it will remember the most excellent solution obtained so far. Every exploration agent chooses a goal prey from the reminiscence of the entire group. Assail and sail vectors for every Russian Haliaeetus pelagicus are then computed in comparison the chosen prey. If the new-fangled location is improved than the preceding location in the reminiscence, then the reminiscence is rationalized. Every Russian Haliaeetus pelagicus arbitrarily chooses its prey in the present iteration from the reminiscence of any other group associate. It is notable that the chosen prey is not essentially to be adjacent or farthest away. Every prey in the reminiscence is allocated or charted to one Russian Haliaeetus pelagicus. Naturally most excellent location visited so far is memorized by Russian Haliaeetus pelagicus. It concomitantly has lure in the direction of attack and on route for sail to explore for superior prey. The fundamentals of the acquired goal spot are arbitrary figures among 0 and 1. It is notable that the sail vector draws the population of Russian Haliaeetus pelagicus in the direction of the region, which is not in the recorded memory. In ERHOA exterior archive, prey precedence condition, and picking of prey are added through multi-objective mode. The fundamental plan is to keep capable solutions in an exterior archive and modernize when procedure continues. Exploration agents are moved in the direction of the stored entities. If the new-fangled solution is conquered by one or more of the present archive entities then the new-fangled solution is removed. Crowding distance value is computed for the stored entities. The departing entity is chosen by roulette wheel selection method, in which the possibility is comparative to value of crowding distance. Prey chosen by a method based on roulette wheel, in which the sparsity counts of the present stored entities are weights and it consequences an elevated possibility for choosing the entities in the area of the facade and less possibility for stored entities in the intense areas. Rationality of ERHOA is confirmed by corroborating in IEEE 30 bus system (with and devoid of L-index). True power loss lessening is achieved. Proportion of true power loss reduction is augmented.

Problem formulation. Power loss minimization is defined by $\min \tilde{F}\left(\overline{d}, \overline{e}\right)$, where $\min$ is minimization of power loss.

Subject to the constraints

$$A\left(\overline{d}, \overline{e}\right) = 0, \;\; B\left(\overline{d}, \overline{e}\right) = 0.$$

Here $\overline{d}$, $\overline{e}$ are control and dependent variables,

$$\overline{d} = \left[VLG_1, \ldots, VLG_{N_g};\;\; QC_1, \ldots, QC_{N_c};\;\; T_1, \ldots, T_{N_T}\right],$$

$$\overline{e} = \left[PG_{slack};\; VL_1, \ldots, VL_{N_L};\;\; QG_1, \ldots, QG_{N_g};\;\; SL_1, \ldots, SL_{N_T}\right],$$

where QC is reactive power compensators; T is a tap setting of transformers; VL_g is level of the voltage; PG_{slack} is slack generator; VL is voltage on transmission lines; QG is generation unit's reactive power; SL is apparent power.

The fitness function $\left(F_1, F_2, F_3\right)$ is designed for power loss lessening (MW), voltage deviancy, voltage constancy index (L-index) is defined by

$$F_1 = P_{\min} = \min\left[\sum_{m}^{N_{TL}} G_m\left[V_i^2 + V_j^2 - 2V_iV_j\cos\varnothing_{ij}\right]\right],$$

$$F_2 = \min\left[\sum_{i=1}^{N_{LB}}\left|VL_k - VL_k^{desired}\right|^2 + \sum_{i=1}^{N_g}\left|QG_K - QG_K^{Lim}\right|^2\right],$$

$$F_3 = \min L_{\max},$$

where N_{TL} is number of transmission line; VL_k is load voltage in k-th load bus; $VL_k^{desired}$ is voltage desired at the k-th load bus; QG_K is reactive power generated at k-th load bus generators; QG_K^{Lim} is reactive power limitation; N_{LB}, N_g are number load and generating units;

$$L_{\max} = \max\left[L_j\right],\ j = 1, \ldots, N_{LB},$$

$$L_j = 1 - \sum_{i=1}^{NPV} F_{ji}\frac{V_i}{V_j},$$

$$F_{ji} = -\left[Y_1\right]^1\left[Y_2\right];$$

$$L_{\max} = \max\left[1 - \left[Y_1\right]^{-1}\left[Y_2\right]\frac{V_i}{V_j}\right].$$

Parity constraints

$$0 = PG_i - PD_i - V_i\sum_{j\in N_B} V_j\left[G_{ij}\cos\left[\varnothing_i - \varnothing_j\right] + B_{ij}\sin\left[\varnothing_i - \varnothing_j\right]\right],$$

$$0 = QG_i - QD_i - V_i\sum_{j\in N_B} V_j\left[G_{ij}\sin\left[\varnothing_i - \varnothing_j\right] + B_{ij}\cos\left[\varnothing_i - \varnothing_j\right]\right].$$

Disparity constraints

$$PG_{slack}^{\min} \le PG_{slack} \le PG_{slack}^{\max},\quad QG_i^{\min} \le QG_i \le QG_i^{\max},\ i \in N_g,$$

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

$$QC^{\min} \le QC \le QC^{\max},\ i \in N_C,\ \left|SL_i\right| \le SL_i^{\max},\ i \in N_{TL},$$

$$VG_i^{\min} \le VG_i \le VG_i^{\max},\ i \in N_g,$$

$$MOF = F_1 + r_iF_2 + uF_3 =$$

$$= F_1 + \left[\sum_{i=1}^{N_L} x_v\left[VL_i - VL_i^{\min}\right]^2 + \sum_{i=1}^{N_G} r_g\left[QG_i - QG_i^{\min}\right]^2\right] + r_fF_3,$$

$$VL_i^{\min} = \begin{cases} VL_i^{\max}\ , VL_i > VL_i^{\max}; \\ VL_i^{\min}, VL_i < VL_i^{\min}, \end{cases}$$

$$QG_i^{\min} = \begin{cases} QG_i^{\max},\ QG_i > QG_i^{\max}; \\ QG_i^{\min}, QG_i < QG_i^{\min}, \end{cases}$$

where *MOF* — multi-objective fitness; r_i is control variables; *u* is dependent variables.

Russian Haliaeetus pelagicus Optimization Algorithm. Russian Haliaeetus pelagicus Optimization Algorithm is designed based on the spiral motion of Russian Haliaeetus pelagicus. Naturally most excellent location visited so far is remembered by Russian Haliaeetus pelagicus. It concurrently has lure in the direction of attack and on route for sail to explore for superior prey.

Russian Haliaeetus pelagicus follow a spiral trajectory for exploration and a straight line lane for assail. It shows proclivity to sail in preliminary phase of hunting and efficiently changeover to further proclivity to assail in the concluding phases. Russian Haliaeetus pelagicus conserve proclivity for both sail and assail in each instant of the voyage. Information about the prey will be shared among the Russian Haliaeetus pelagicus's.

Russian Haliaeetus pelagicus "*i*" arbitrarily choose the prey in iterations of an additional Russian Haliaeetus pelagicus "*f*". It loops in the region of the most excellent location visited by Russian Haliaeetus pelagicus "*f*". Russian Haliaeetus pelagicus "*i*" chooses the loop based on its individual memory and it defined as

$$f \in \left\{1, 2, 3, \ldots, \mathit{Population\ size}\right\}.$$

Russian Haliaeetus pelagicus should select a prey to carry out the sail and assail function in all iterations. Prey is scientifically modeled based on the most excellent solutions found by the group of Russian Haliaeetus pelagicus and it will remember the most excellent solution obtained so far.

Every exploration agent chooses a goal prey from the reminiscence of the entire group. Assail and sail vectors for every Russian Haliaeetus pelagicus are then computed in comparison the chosen prey. If the new-fangled location is improved than the preceding location in the reminiscence, then the reminiscence is rationalized. Every Russian Haliaeetus pelagicus arbitrarily choose its prey in the present iteration from the reminiscence of any other group associate. It is notable that the chosen prey is not essentially to be adjacent or farthest away. Every prey in the reminiscence is allocated or charted to one Russian Haliaeetus pelagicus.

The assail (exploitation phase) is modelled by a vector starting from the present position and end in the location of the prey in the Russian Haliaeetus pelagicus memory:

$$\text{Assail}\left(\vec{A}_i\right) = \vec{H}_i^* - \vec{H}_i, \tag{1}$$

where $\vec{H}_i^*$ is the most excellent loation visited by Russian Haliaeetus pelagicus; $\vec{H}_i$ is the present position of Russian Haliaeetus pelagicus.

Sail vector is computed based on the assail vector. Sail vector is a tangent to the loop and vertical to the assail vector. The sail can be linear pace of Russian Haliaeetus pelagicus in comparison the prey. The sail vector in n-dimensions is situated within the tangent plane in loop in order compute the sail vector:

$$q_1 a_1 + q_2 a_2 + \ldots + q_n a_n = m \Rightarrow \sum_{j=1}^{n} q_j a_j = m, \tag{2}$$

$$\vec{Q} = \left[q_1, q_2, \ldots, q_n\right]; \tag{3}$$

$$\vec{A} = \left[a_1, a_2, \ldots, a_n\right], \tag{4}$$

$$\vec{S} = \left[s_1, s_2, \ldots, s_n\right], \tag{5}$$

$$m = \vec{Q} \cdot \vec{S} = \sum_{i=1}^{n} q_j s_j, \tag{6}$$

$$\sum_{j=1}^{n} a_j h_j = \sum_{j=1}^{n} a_j^t h_j^*, \tag{7}$$

$$H^* = \left[h_1^*, h_2^*, \ldots, h_n^*\right]. \tag{8}$$

Arbitrarily pick one variable out of “n” parameters as the unchanging variable. Directory of the chosen parameter is k. Then the unchanging is defined as

$$u_k = \frac{m - \sum_{j, j \neq k} a_j}{a_k}, \tag{9}$$

u_k goal point K,

$$\vec{U}_i = \left(u_1 = Rand,\ u_2 = Rand, \ldots,\ u_k = \frac{m - \sum_{j, j \neq k} a_j}{a_k}, \ldots,\ u_n = Rand \right). \tag{10}$$

At this point that the goal point is defined, the sail vector is computed for the Russian Haliaeetus pelagicus “i” in the iteration “t”. The fundamentals of the acquired goal spot are arbitrary figures among 0 and 1. It is notable that the sail vector draws the population of Russian Haliaeetus pelagicus in the direction of the region which is not in the recorded memory; consequently, it accentuate the exploration segment.

The dislodgments of the Russian Haliaeetus pelagicus encompass of assail and sail vector. Russian Haliaeetus pelagicus step vector in "*i*" th iteration "*t*" is defined as

$$\Delta h_i = \overrightarrow{Rand}_1 s_a^t \frac{\vec{A}_i}{\|\vec{A}_i\|} + \overrightarrow{Rand}_2 s_c^t \frac{\vec{U}_i}{\|\vec{U}_i\|}, \tag{11}$$

where s_a^t is assail coefficient in iteration "*t*"; s_c^t is sail coefficient in iteration "*t*";

$$\|\vec{A}_i\| = \sqrt{\sum_{j=1}^{n} a_j^2}; \tag{12}$$

$$\|\vec{U}_i\| = \sqrt{\sum_{j=1}^{n} u_j^2}. \tag{13}$$

In iteration $t+1$ the position of Russian Haliaeetus pelagicus is computed by

$$h^{t+1} = h^t + \Delta h_i^t. \tag{14}$$

If the fitness of Russian Haliaeetus pelagicus "*i*" new-fangled position is better than the position with reference to its memory, then it replaced. Or else, the memory relics as integral part, but Russian Haliaeetus pelagicus will exist in the new-fangled position. In the new-fangled iteration, Every Russian Haliaeetus pelagicus arbitrarily pick a Russian Haliaeetus pelagicus from the population to the loop in the region of most excellent visited position, compute assail, sail vector and lastly step vector with new-fangled position for the subsequent iteration. This circle is implemented in anticipation of satisfying the end condition.

Russian Haliaeetus pelagicus demonstrate a superior proclivity to sail in the preliminary phase of the hunting voyage and illustrate an elevated proclivity to assail in the concluding phase, which match up to additional exploration in preliminary iterations and extra exploitation in the concluding iterations.

The procedure begins with small s_a and elevated s_u. When iterations progress, s_a is regularly amplified while s_u is steadily reduced and *t* defined as follows:

$$s_a = s_a^0 + \frac{t}{T}\left|s_a^T - s_a^0\right|,$$
$$s_u = s_u^0 + \frac{t}{T}\left|s_u^T - s_u^0\right|, \qquad (15)$$

where t, T are current and maximum iterations; s_a^0, s_a^T are preliminary and final values; s_u^0, s_u^T are preliminary and final values.

Algorithm

a. Start
b. Initialize the Russian Haliaeetus pelagicus population
c. Estimate the fitness function
d. Initialize the memory of the Russian Haliaeetus pelagicus population
e. Initialize s_a, s_u
f. For each iteration “t”
g. Update s_a and s_u
h. Formula (15)
i. For each Russian Haliaeetus pelagicus “t”
j. Arbitrarily choose a prey from the memory of the Russian Haliaeetus pelagicus population
k. Compute assail vector
l. Formula (1)
m. If assail vector’s extent (1) is not equivalent to zero
n. Compute the sail vector
o. (2)
p. (3)
q. (4)
r. (5)
s. (6)
t. (7)
u. (8)
v. (9)
w. (10)
x. Calculate the step vector
y. (11)
z. (12)
aa. (13)
bb. (14)
cc. Modernize the position
dd. (14)

ee. Calculate fitness value for the new-fangled position

ff. If fitness is superior to the Russian Haliaeetus pelagicus "i" positions fitness value memory

gg. Swap the new-fangled position with the Russian Haliaeetus pelagicus "i" memory

hh. Update $t = t + 1$

ii. End

In the ERHOA exterior archive, prey precedence condition, and picking of prey are included through multi-objective mode. The fundamental plan is to keep capable solutions in an exterior archive and modernize when procedure continues. Exploration agents are moved in the direction of the stored entities. If the new-fangled solution is conquered by one or more of the present archive entities then the new-fangled solution is removed. If the new-fangled solution is not ruled over the present entities of the stored one and the records are not occupied, basically append the new-fangled position to the store. If the new-fangled position is not ruled over the present entities of the stored one then arbitrarily choose one of the stored entities and replace with new-fangled solution. An appraisal is required to define the concentration of the close to region for every entity of the stored one. Crowding distance included and defined by [17–23]:

$$CD_i = \frac{1}{n} \sum_{j \in J} \frac{\left(f_{i+1,j} - f_{i,j}\right) - \left(f_{i,j} - f_{i-1,j}\right)}{f_j^{\max} - f_j^{\min}}, \tag{16}$$

where $f_{i,j}$, $f_{i+1,j}$, $f_{i-1,j}$ are the stored entities.

Crowding distance value is computed for the stored entities. The departing entity is chosen by roulette wheel selection method, in which the possibility is comparative to value of crowding distance. The new-fangled counts (SC_i) are used for the roulette wheel process is defined as

$$SC_i = 1 - CD_i. \tag{17}$$

Prey chosen by a method based on roulette wheel, in which the sparsity counts of the present stored entities are weights and it consequences an elevated possibility for choosing the entities in the area of the facade and less possibility for stored entities in the intense areas.

Algorithm

a. Start

b. Initialize the Russian Haliaeetus pelagicus population

c. Estimate the fitness function
d. Initialize the memory of the Russian Haliaeetus pelagicus population
e. Initialize s_a, s_u
f. For each iteration "*t*"
g. Update s_a and s_u
h. Formula (15)
i. For each Russian Haliaeetus pelagicus "*t*"
j. Arbitrarily choose a prey from the memory of the Russian Haliaeetus pelagicus population
k. Compute assail vector
l. (1)
m. If assail vector's extent (215) is not equivalent to zero
n. Compute the sail vector
o. (2)
p. (3)
q. (4)
r. (5)
s. (6)
t. (7)
u. (8)
v. (9)
w. (10)
x. Calculate the step vector
y. (11)
z. (12)
aa. (13)
bb. (14)
cc. Modernize the position
dd. (14)
ee. Calculate fitness value for the new-fangled position
ff. If the new-fangled position is not conquered the present stored entities
gg. If the exterior store is not occupied
hh. Append the new-fangled solution to the store
ii. Otherwise
jj. Compute the expanse
kk. (16)
ll. (17)
mm. Departing entity is chosen by roulette wheel selection method
nn. Swap the departing solution with the new-fangled one

oo. Update $t = t + 1$

pp. End

Simulation results. With considering *L*-index (voltage stability), RHOA and ERHOA is substantiated in IEEE 30 bus system [24]. Appraisal of loss has been done with PSO, amended PSO, enhanced PSO, widespread learning PSO, Adaptive Genetic Algorithm, Canonical Genetic Algorithm, Enriched Genetic Algorithm, Hybrid PSO-Tabu search (PSO-TS), Ant Lion (ALO), Quasi-Oppositional Teaching Learning Based (QOTBO), Improved Stochastic Fractal Search Optimization Algorithm (ISFS), Harmony Search (HS), Improved Pseudo-Gradient Search Particle Swarm Optimization and Cuckoo Search algorithm. Power loss abridged competently and proportion of the power loss lessening has been enriched. Predominantly voltage constancy enrichment achieved with minimized voltage deviancy. In Table 1 shows the loss appraisal, Table 2 shows the voltage deviancy evaluation and Table 3 gives the *L*-index assessment. Figures 1 to 3 gives graphical appraisal.

Table 1

Assessment of true power loss lessening

Technique	True power loss, MW	Technique	True power loss, MW
Standard PSO-TS [10]	4.5213	Standard PSO [13]	4.9239
Basic TS [10]	4.6862	HAS [13]	4.9059
Standard PSO [10]	4.6862	Standard FS [14]	4.5777
ALO [11]	4.5900	ISFS [14]	4.5142
QOTLBO [12]	4.5594	Standard FS [16]	4.5275
TLBO [12]	4.5629	RHOA	4.5004
Standard GA [13]	4.9408	ERHOA	4.4986

The appraisal of power loss and assessment done with Basic PSO-TS, Standard TS, Basic PSO, ALO [11], Basic QOTLBO, Standard TLBO [12], Standard GA, Basic PSO, HAS [13], Standard FS, ISFS [14] and Standard FS [16] show in Table 1 and Fig. 1.

The evaluation of voltage deviancy and assessment done with Basic PSO-TVIW, Basic PSO-TVAC, Standard PSO-TVAC, Basic PSO-CF, PG-PSO, SWT-PSO, PGSWT-PSO, MPG-PSO, QO-TLBO, TLBO [12], Standard FS, ISFS [14] and Standard FS [16] show in Table 2 and Fig. 2.

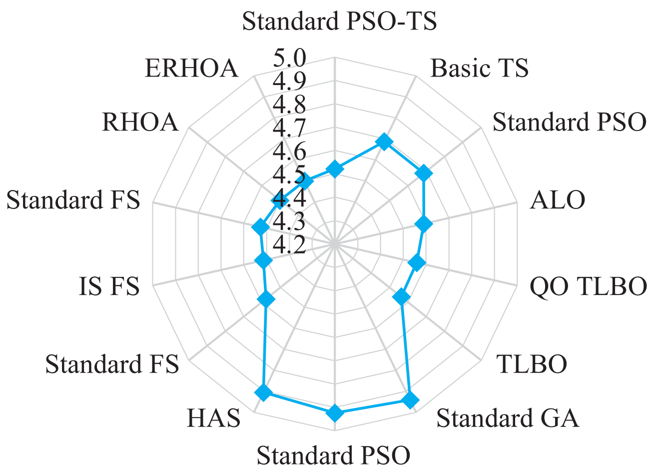

Fig. 1. Appraisal of factual power loss

Table 2

Evaluation of voltage deviation

Technique	Voltage deviation, PU	Technique	Voltage deviation, PU
Standard PSO-TVIW [15]	0.1038	QOTLBO [12]	0.0856
Standard PSO-TVAC [15]	0.2064 / 0.1354	TLBO [12]	0.0913
Standard PSO-CF [15]	0.1287	Standard FS [14]	0.1220
PG-PSO [15]	0.1202	ISFS [14]	0.0890
SWT-PSO [15]	0.1614	Standard FS [16]	0.0877
PGSWT-PSO [15]	0.1539	RHOA	0.0846
MPG-PSO [15]	0.0892	ERHOA	0.0837

The voltage constancy and assessment done with Basic PSO-TVIW, Basic PSO-TVAC, Standard PSO-TVAC, Basic PSO-CF, PG-PSO, SWT-PSO, PGSWT-PSO, MPG-PSO [15], QOTLBO, Standard TLBO [12], ALO, ABC, Standard GWO, Basic BA [11], Standard FS, ISFS [14] and Standard FS [16] show in Table 3 and Fig. 3.

Then Projected RHOA and ERHOA are corroborated in IEEE 30 bus test system deprived of *L*-index. Loss appraisal is shown in Table 4. Figure 4 gives graphical appraisal between the approaches with orientation to true power loss.

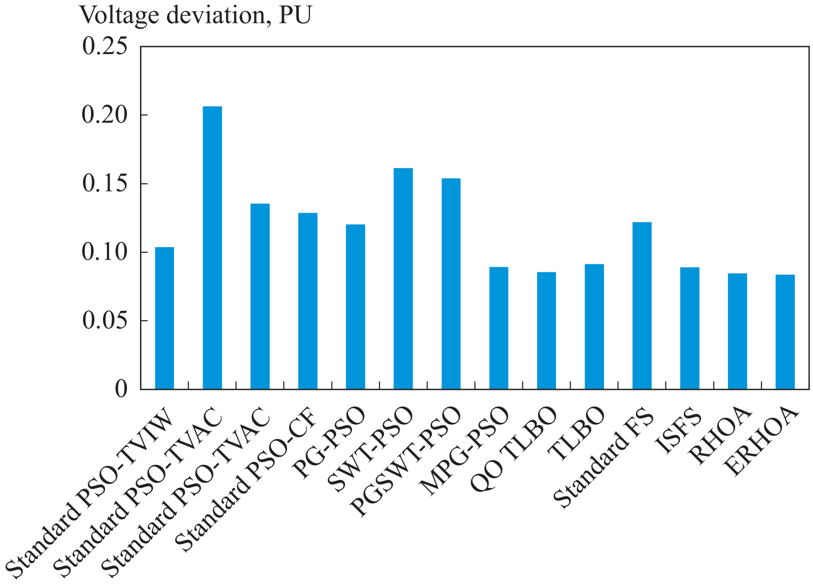

Fig. 2. Appraisal of voltage deviation

Table 3

Assessment of voltage constancy

Technique	Voltage constancy, PU	Technique	Voltage constancy, PU
Standard PSO-TVIW [15]	0.1258	ALO [11]	0.1161
Standard PSO-TVAC [15]	0.1499 / 0.1271	ABC [11]	0.1161
Standard PSO-CF [15]	0.1261	GWO [11]	0.1242
PG-PSO [15]	0.1264	BA [11]	0.1252
Standard WT-PSO [15]	0.1488	Basic FS [14]	0.1252
PGSWT-PSO [15]	0.1394	ISFS [14]	0.1245
MPG-PSO [15]	0.1241	S-FS [16]	0.1007
QOTLBO [12]	0.1191	RHOA	0.1003
TLBO [12]	0.1180	ERHOA	0.1000

The actual power loss appraisal for IEEE 30 bus system without considering voltage constancy and assessment done with base case value, M-PSO [24], Basic PSO [23], EP [21], Standard GA [22], PSO [25], DEPSO [25] and JAYA [25] show in Table 4 and Fig. 4.

The convergence characteristics of RHOA and ERHOA show in Table 5. Figure 5 shows the graphical representation of the characteristics.

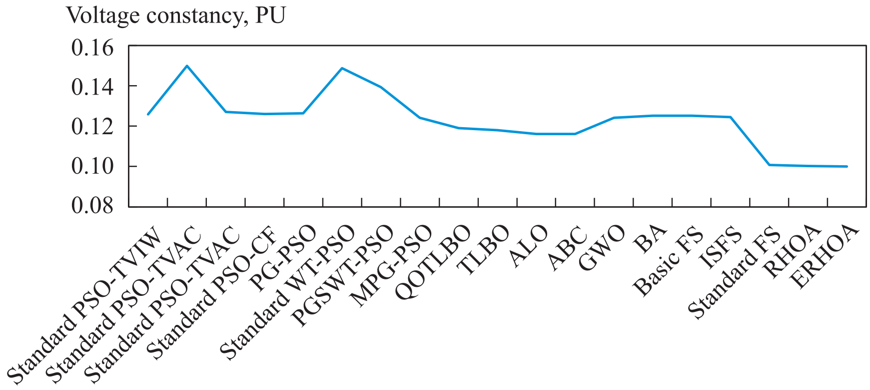

Fig. 3. Appraisal of voltage constancy

Table 4

Assessment of true power loss

Parameter	True power loss, MW	Proportion of lessening in power loss
Base case value [28]	17.5500	0
Amended PSO[28]	16.0700	8.40000
Standard PSO [27]	16.2500	7.40000
Standard EP [25]	16.3800	6.60000
Standard GA [26]	16.0900	8.30000
Basic PSO [29]	17.5246	0.14472
DEPSO [29]	17.5200	0.17094
JAYA [29]	17.5360	0.07977
RHOA	14.0900	19.7150
ERHOA	13.8900	20.8547

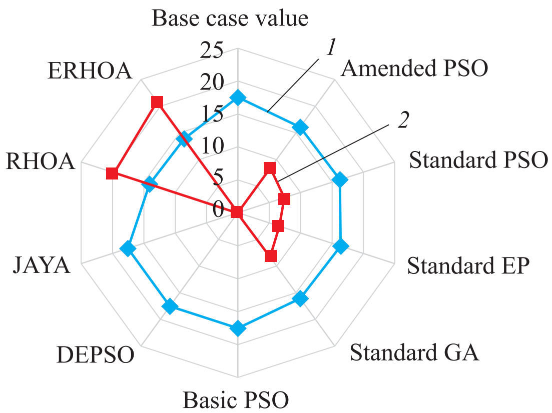

Fig. 4. Appraisal of true power loss:
1 is factual power loss, MW; *2* is proportion of lessening in power loss

Table 5

Convergence characteristics

Technique	True power loss with / without *L*-index, MW		Time with / without *L*-index, s		Number of iterations with / without *L*-index	
RHOA	4.5004	14.09	19.60	16.02	29	25
ERHOA	4.4986	13.89	21.05	17.99	33	29

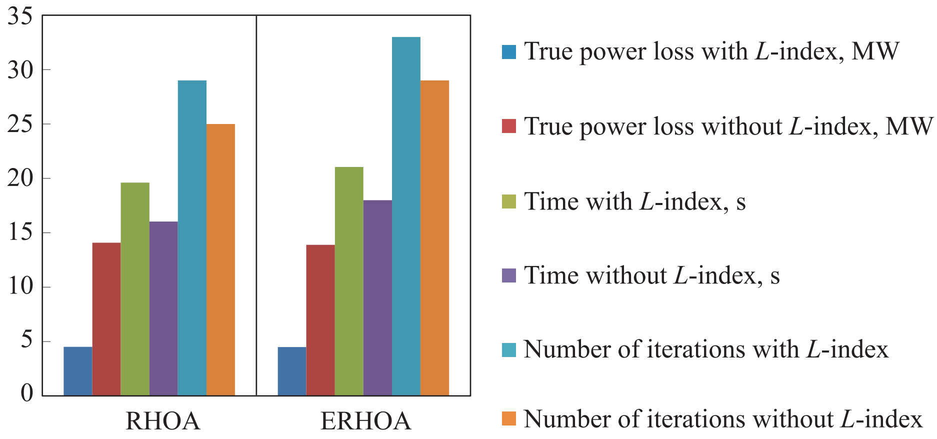

Fig. 5. Convergence characteristics of RHOA and ERHOA

Conclusion. Russian Haliaeetus pelagicus Optimization Algorithm and ERHOA abridged the power loss competently. Russian Haliaeetus pelagicus should select a prey to carry out the sail and assail function in all iterations. Prey is scientifically modelled based on the most excellent solutions found by the group of Russian Haliaeetus pelagicus and it remembered the most excellent solution obtained so far. Every exploration agent chooses a goal prey from the reminiscence of the entire group. Assail and sail vectors for every Russian Haliaeetus pelagicus are then computed in comparison the chosen prey. If the new-fangled location is improved than the preceding location in the reminiscence, then the reminiscence is rationalized. Every Russian Haliaeetus pelagicus arbitrarily choose its prey in the present iteration from the reminiscence of any other group associate. It is notable that the chosen prey is not essentially to be adjacent or farthest away. Every prey in the reminiscence is allocated or charted to one Russian Haliaeetus pelagicus. Russian Haliaeetus pelagicus Optimization Algorithm is enhanced by adding the features: exterior archive, prey precedence condition, and picking of prey through multi-objective mode. The fundamental plan is to keep capable solutions in an exterior archive and modernize when procedure continues. Exploration agents are moved in the direction of the stored entities. If the new-fangled solution is conquered by one or more of the present archive entities then the new-fangled solution is removed. If the new-fangled solution is not ruled over the present entities of the stored one and the records are not occupied, basically append the new-fangled position to the store. If the new-fangled position is not ruled over the present entities of the stored one then arbitrarily choose one of the stored entities and replace with new-fangled solution. An appraisal is required to define the concentration of the close to region for every entity of the stored one. Crowding distance value is computed for the stored entities. The departing entity is chosen by reselection method, in which the possibility is comparative to value of crowding distance. Prey is chosen by a method based on roulette wheel, in which the sparsity counts of the present stored entities are weights and it consequences an elevated possibility for choosing the entities in the area of the facade and less possibility for stored entities in the intense areas. Convergence characteristics show the better performance of the proposed ERHOA. Assessment of power loss has been done with other customary reported algorithms.

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