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REAL POWER LOSS REDUCTION AND VOLTAGE STABILITY ENRICHMENT BY EXTREME LEARNING MACHINE BASED PHOENICOPARRUS SEARCH, QUANTUM-INSPIRED MYRMICINAE, HERPESTES, PHILANDER OLROGI AND CHAOTIC BASED SIMIEN FOX OPTIMIZATION ALGORITHMS

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Abstract

In this paper Extreme learning machine based Phoenicoparrus search (ELMPS) optimization algorithm, quantum-inspired Myrmicinae evolutionary algorithm (QIMEA), Herpestes optimization (HO) algorithm, Philander olrogi optimization (PO) algorithm and Chaotic based Simien Fox optimization (CSFO) algorithm has been applied to solve the power loss lessening problem. Phoenicoparrus search (PS) optimization algorithm is stimulated by the Phoenicoparrus itinerant and scavenging behaviour. Then the extreme learning machine based Phoenicoparrus search (ELMPS) optimization algorithm is designed. Quantum-inspired Myrmicinae evolutionary algorithm (QIMEA) design is imitated by the actions of Myrmicinae. In HO algorithm with the reference to the rate of breed centre of group and sex, Herpestes group individuals will perform the movement. Then Philander olrogi optimization algorithm has been designed based on the track and preying actions of Philander olrogi. Based on the natural actions of Simien Fox proposed CSFO algorithm is designed. Chaotic sequences are integrated into the Simien Fox optimization algorithm and it will enhance the exploration and exploitation. Legitimacy of proposed algorithms is corroborated in standard IEEE test systems. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained

Keywords

Optimal reactive power, transmission loss, equipoise state, extreme learning machine, phoenicoparrus, quantum, myrmicinae, herpestes, philander olrogi, chaotic, simien fox

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Introduction. Power problem is envisioned as one of the outstanding environments for benign and economic operation of system. It is flawless by correct association of the group kit used to deal with up the power flow with the goal mouth of weakening the power losses and development the power skeleton of the organization. Zhu *et al* [1] solved the optimal reactive power control using modified interior point method. Quintana *et al* [2] did reactive-power dispatch by successive quadratic programming. Jan *et al* [3] did application of the fast Newton — Raphson economic dispatch and reactive power/voltage dispatch by sensitivity factors to optimal power flow. Terra *et al* [4] did security-constrained reactive power dispatch. Grudinin [5] did Reactive power optimization using successive quadratic programming method. Mohamed Ebeed *et al* [6] did the optimal reactive power dispatch using marine predators algorithm considering the uncertainties in load and wind-solar generation systems. Zahir Sahli *et al* [7] did reactive power dispatch optimization with voltage profile improvement using an efficient hybrid algorithm. Davoodi *et al* [8] did a novel fast semidefinite programming-based approach for optimal reactive power dispatch. Bingane *et al* [9] applied tight-and-cheap conic relaxation for the optimal reactive power dispatch problem. Sahli *et al* [10] applied hybridized PSO-Tabu exploration for the problem. Mouassa *et al* [11] applied ant lion algorithm for solving the problem. Mandal *et al* [12] solved the problem by using quasi-oppositional teaching. Khazali *et al* [13] solved the problem by harmony search procedure. Tran *et al* [14] solved problem by innovative enhanced stochastic fractal search procedure. Polprasert *et al* [15] solved the problem by using enhanced pseudo-gradient pursuit particle swarm optimization. Thanh *et al* [16] solved the problem by an operative metaheuristic procedure. Raghuwanshi *et al* [17] did class imbalance learning using under bagging based kernelized extreme learning machine. Yu X. *et al* [18] had done dual-weighted kernel extreme learning machine for hyperspectral imagery classification. Han *et al* [19] did hyperspectral image classification based on multiple reduced kernel extreme learning machine. From Illinois Center [20] for a Smarter Electric Grid (ICSEG) IEEE 30 bus system data obtained. Dai *et al* [21] used seeker optimization procedure for solving the problem. Subbaraj *et al* [22] used self-adaptive real coded genetic procedure to solve the problem. Pandya *et al* [23] applied particle swarm optimization to solve the problem. Ali Nasser Hussain *et al* [24] applied amended particle swarm optimization to solve the problem. Vishnu *et al* [25] applied an enhanced particle swarm optimization to solve the problem. Omelchenko I.N. *et al* [26] did development of a design algorithm for the logistics system of product distribution of the mechanical engineering enterprise. Omelchenko I.N. *et al* [27] did the work on organization of logistic systems of scientific productions. Omelchenko I.N. *et al* [28] solved the problems and organizational and technical solutions of processing management problems of material and technical resources in a design-oriented organization. Khunkitti *et al* [29] solved multi-objective optimal power flow problems based on slime mould algorithm. Diab *et al* [30] solved multi-objective optimal power flow control of electrical transmission networks using intelligent meta-heuristic optimization techniques. Surender Reddy [31] solved optimal reactive power scheduling using cuckoo search algorithm. Reddy [32] did faster evolutionary algorithm based optimal power flow using incremental variables. Davidchack *et al* [33] had done complete detection of unstable periodic orbits in chaotic systems. Inoue *et al* [34] did application of chaos degree to some dynamical systems chaos. In this paper extreme learning machine based phoenicoparrus search (ELMPS) optimization algorithm, quantum-inspired myrmicinae evolutionary algorithm (QIMEA), herpestes optimization (HO) algorithm, Philander olrogi optimization (PO) algorithm and chaotic based simien fox optimization (CSFO) algorithm are applied to solve the loss lessening problem. Phoenicoparrus search (PS) optimization algorithm is stimulated by the phoenicoparrus itinerant and scavenging behaviour. Phoenicoparrus are companionable itinerant birds that forage primarily on algae, minor larvae and bug caterpillars. Phoenicoparrus search optimization algorithm institutes the analogous scavenging prototypical and relocation exemplary. Phoenicoparrus croon to each other to connect their position, in addition to the accessibility of nutrition in that position. Quantum-inspired Myrmicinae evolutionary algorithm design is imitated by the actions of Myrmicinae. Queens are the only female Myrmicinae with reproductive capabilities. In HO algorithm arithmetical version of a Herpestes groups consider only single control parameter (*M*); which symbolize the preliminary population size. When both exploration and exploitation not balanced then optimal solution cannot be reached. In PO Algorithm tracking and combating action of Philander olrogi has been scientifically modelled to solve the problem. Chaotic based CSFO is designed based on the natural actions of Simien Fox. Chaotic sequences are integrated into the Simien Fox optimization algorithm (entitled as chaotic based CSFO algorithm) and it will enhance the exploration and exploitation. In this paper tinkerbell chaotic map engendering standards are implemented. Legitimacy of the ELMPS optimization algorithm, QIMEA, HO algorithm, PO algorithm and CSFO algorithm are corroborated in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained.

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

$B\left(\overline{d},\overline{e}\right)=0$, d, e are control and dependent variables, $d=\left[VLG_1,\ldots,VLG_{Ng};\ QC_1,\ldots,QC_{Nc};\ T_1,\ldots,T_{NT}\right]$; $e=\left[PG_{slack};\ VL_1,\ldots,VL_{NLoad};\ QG_1,\ldots,QG_{Ng};\ SL_1,\ldots,SL_{NT}\right]$. Here QC is reactive power compensators; T is tap setting of transformers; PG_{slack} is slack generator; VL_g is level of the voltage; 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 (MW) lessening, voltage deviancy, voltage constancy index (L-index) is defined by:

$$f_1 = P_{\min} = \min\left[\sum_{m}^{NTL} G_m\left[V_i^2+V_j^2-2V_iV_j\cos Ø_{ij}\right]\right];$$

$$f_2 = \min\left[\sum_{i=1}^{N_{LB}}\left|VL_k - VL_k^{desired}\right|^2 + \sum_{i=1}^{Ng}\left|QG_K - QK_G^{\lim}\right|^2\right];$$

$$f_3 = \min L_{\max},$$

where NTL 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; $QK_G^{\lim}$ is reactive power limitation; N_{LB}, Ng 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:

$$0 = PG_i - PD_i - V_i\sum_{j\in NB} V_j\left[G_{ij}\cos\left[Ø_i-Ø_j\right]+B_{ij}\sin\left[Ø_i-Ø_j\right]\right];$$

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

Disparity constraints:

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

$$VL_i^{\min}\le VL_i\le VL_i^{\max},\ i\in NL,\quad T_i^{\min}\le T_i\le T_i^{\max},\ i\in NT,$$

$$QC^{\min}\le QC\le QC^{\max},\ i\in NC,\ \left|SL_i\right|\le SL_i^{\max},\ i\in NTL,$$

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

Multi objective fitness function

$$MOF = f_1 + r_i f_2 + u f_3 =$$
$$= f_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{\min} \right]^2 + \sum_{i=1}^{Ng} r_g \left[QG_i - QG_i^{\min} \right]^2 \right] + r_f f_3,$$

u is dependent variables;

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

Extreme learning machine based phoenicoparrus search optimization algorithm. Phoenicoparrus search optimization algorithm is simulated by the Phoenicoparrus itinerant and scavenging behaviour. At that moment the supreme distance of the Phoenicoparrus bill probe in scavenging actions can be enumerated as follows: $\left| H_1 zl_j + \varepsilon_2 z_{ij} \right|$, where $\varepsilon_2 \in [-1, 1]$; H_1 will follow the regular customary arbitrary distribution; $H_2 \left| H_1 zl_j + \varepsilon_2 z_{ij} \right|$, H_2 will follow the regular customary arbitrary distribution; $\varepsilon_1 zl_j$, where $\varepsilon_1 \in [-1, 1]$; $l_{ij}^t = \varepsilon_1 zl_j^t + H_2 \left| H_1 zl_j^t + \varepsilon_2 zl_j^t \right|$. Then the equation for modernizing the position of Phoenicoparrus scavenging actions is expressed as

$$z_{ij}^{t+1} = \frac{\left(z_{ij}^t + \varepsilon_1 zl_j^t + H_2 \left| H_1 zl_j^t + \varepsilon_2 zl_j^t \right| \right)}{D}. \tag{1}$$

Here z_{ij}^{t+1} specify the i-th position of Phoenicoparrus in j-th dimension of $t+1$ iteration; z_{ij}^t specify the i-th position of Phoenicoparrus in j-th dimension of t iteration; zl_j^t indicate the j-th dimension of Phoenicoparrus which have excellent fitness; D is dispersal factor, $D = D(n)$, $H_1, H_2 = N(0, 1)$,

$$z_{ij}^{t+1} = z_{ij}^t + \omega \left(zl_j^t - z_{ij}^t \right), \tag{2}$$

$\omega = N(0, n) \rightarrow$ is Gaussian arbitrary number.

Step procedure of PS optimization algorithm:

a. Initialize the population
b. The amount of scavenging Phoenicoparrus in the i-th iteration of Phoenicoparrus populace regeneration is articulated mathematically
c. Formula: $RP_{rege} = \text{random}[0, 1] P (1 - RP_l)$
d. In primary part of iteration, the quantity of relocating Phoenicoparrus is designed

e. $RP_o = RP_l P$
f. In primary part of iteration, the quantity of relocating Phoenicoparrus is designed
g. $RP_t = P - RP_o - RP_{rege}$
h. The appropriateness (fitness) rate of Phoenicoparrus is computed, and the populace of Phoenicoparrus is classified rendering to the fitness rate of individual Phoenicoparrus
i. The previous Phoenicoparrus RP_l possesses small fitness value and the past Phoenicoparrus RP_t possesses great fitness rate are considered as relocated Phoenicoparrus, however the remaining are considered as scavenging Phoenicoparrus
j. Modernize the relocating Phoenicoparrus
k. Formula (2)
l. Streamline the scavenging Phoenicoparrus
m. Formula (1)
n. Confirm the boundlimits of Phoenicoparrus
o. If maximum iteration number reached then go to next step or else go to step "b"
p. Output the optimum solution
q. End

Algorithm of PS optimization algorithm:
a. Start
b. Initialize the population
c. Grade the fitness rate and discover the present preeminent entity
d. z_{best}; $t \leftarrow 1$
e. while $\left(t \leq \text{iteration}_{\max}\right)$ do
f. $r \leftarrow \text{random}\left[0,1\right]$
g. $RP_{rege} \leftarrow \text{random } P\left(1 - RP_1\right)$
h. $RP_o \leftarrow RP_l$
i. $RP_t \leftarrow P - RP_o - RP_{rege}$
j. For $i \leftarrow 1$ to RP_l do
k. For $j \leftarrow 1$ to dimension (n) do
l. Streamline the position of Phoenicoparrus
m. Formula (2)
n. End for
o. End for

p. For $i \leftarrow 1 + RP_o$ to $RP_o + RP_{rege}$ do
q. For $j \leftarrow 1$ to dimension(n) do
r. Rationalize the position of Phoenicoparrus
s. Formula (1)
t. End for
u. End for
v. For $i \leftarrow 1 + RP_o + RP_{rege}$ to P do
w. For $j \leftarrow 1$ to dimension(n) do
x. Modernize the position of Phoenicoparrus
y. Formula (2)
z. End for
aa. End for
bb. For $i \leftarrow 1$ to P do // bound limits finding
cc. For $j \leftarrow 1$ to dimension(n) do
dd. if $z_{ij}^t >$ upper bound, then
ee. $z_{ij}^t \leftarrow$ upper bound
ff. End if
gg. if $z_{ij}^t <$ lower bound, then
hh. $z_{ij}^t \leftarrow$ lower bound
ii. End if
jj. End for
kk. End for
ll. Grade the fitness rate and discover the present preeminent entity
mm. $t \leftarrow t + 1$
nn. End while
oo. Return the z_{best}
pp. End

Extreme learning machine (ELM) is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer [17–19]. The associating neurons weight matrix of input to hidden layer is demarcated as

$$Weight(Wit) = \begin{bmatrix} wit_1^t \\ wit_2^t \\ \vdots \\ wit_l^t \end{bmatrix} = \begin{bmatrix} wit_{11} & \dots & wit_{1n} \\ \vdots & \ddots & \vdots \\ wit_{L1} & \dots & wit_{Ln} \end{bmatrix}.$$

Neurons weight matrix:

$$nwtm\,\beta = \begin{bmatrix} nwtm\,\beta_1^t \\ nwtm\,\beta_2^t \\ \vdots \\ nwtm\,\beta_l^t \end{bmatrix} = \begin{bmatrix} nwtm\,\beta_{11} & \dots & nwtm\,\beta_{1n} \\ \vdots & \ddots & \vdots \\ nwtm\,\beta_{L1} & \dots & nwtm\,\beta_{Ln} \end{bmatrix}.$$

Neurons hidden layer bias vector:

$$bsvr = \begin{bmatrix} bsvr_1 \\ bsvr_2 \\ \vdots \\ bsvr_L \end{bmatrix}_{L\times 1}.$$

For N impulsive

$$(B_i, F_i);\; F_i = [F_{i1}, F_{i2}, \dots, F_{idn}]^E \in MN^{dn},\;\; C_i = [C_{i1}, C_{i2}, \dots, C_{idn}]^E \in MN^{dn},$$

$$C = \begin{bmatrix} C_1^t \\ C_2^t \\ \vdots \\ C_l^t \end{bmatrix} = \begin{bmatrix} C_{11} & \dots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{L1} & \dots & C_{Ln} \end{bmatrix}, \quad \sum_{i=1}^{N} nwtm\,\beta_i k\left(\omega_i F_j + a_i\right) = C_j,\; j = 1, 2, \dots, N,$$

$$O\left(nwtm\,\beta\right) = C,$$

$$O\left(F_1, \dots, F_L; \omega_1, \dots, \omega_L; a_1, \dots, a_l\right) = \begin{bmatrix} k\left(\omega_1 F_1 + a_1\right) & \dots & k\left(\omega_L F_1 + a_L\right) \\ \vdots & \ddots & \vdots \\ k\left(\omega_1 F_N + a_1\right) & \dots & k\left(\omega_L F_N + a_L\right) \end{bmatrix},$$

$$nwtm\;\beta = O^{-1}C.$$

The procedure of ELMPS optimization algorithm is defined as follows:

a. Start
b. Input the data
c. Engender the test and training set
d. Grade the fitness rate and discover the present preeminent entity
e. $z_{best};\; t \leftarrow 1$
f. while $\left(t \le \text{iteration}_{\max}\right)$ do
g. $r \leftarrow \text{random}\,[0, 1]$

h. $RP_{rege} \leftarrow \text{random } P\left(1 - RP_1\right)$
i. $RP_o \leftarrow RP_l$
j. $RP_t \leftarrow P - RP_o - RP_{rege}$
k. For $i \leftarrow 1$ to RP_l do
l. For $j \leftarrow 1$ to dimension (n) do
m. Streamline the position of Phoenicoparrus
n. Formula (2)
o. End for
p. End for
q. For $i \leftarrow 1 + RP_o$ to $RP_o + RP_{rege}$ do
r. For $j \leftarrow 1$ to dimension (n) do
s. Rationalize the position of Phoenicoparrus
t. Formula (1)
u. End for
v. End for
w. For $i \leftarrow 1 + RP_o + RP_{rege}$ to P do
x. For $j \leftarrow 1$ to dimension (n) do
y. Modernize the position of Phoenicoparrus
z. Formula (1)
aa. End for
bb. End for
cc. For $i \leftarrow 1$ to P do // bound limits finding
dd. For $j \leftarrow 1$ to dimension (n) do
ee. *if* $z_{ij}^t >$ upper bound, then
ff. $z_{ij}^t \leftarrow$ upper bound
gg. End if
hh. *if* $z_{ij}^t <$ lower bound, then
ii. $z_{ij}^t \leftarrow$ lower bound
jj. End if
kk. End for
ll. End for
mm. Fix ELM input weights and hidden biases
nn. ELM testing
oo. Return the z_{best}
pp. End

Quantum-inspired Myrmicinae evolutionary algorithm. Quantum-inspired Myrmicinae evolutionary algorithm design is imitated by the actions of Myrmicinae. Chromosome specify the colony member is indicated as: $A_i = Ce_i Uf_i$, where A_i indicate the population individuals; f_i is the fitness function.

A common function G allocates the fitness function to every element of A:

$$G = U_{i \in N} f_i, \;\; G : A_{\downarrow} \to G_{\downarrow}.$$

Here

$$A_{\downarrow} = \left\{ A_i : i \in N, A_i \geq A_{i+1} \right\} = \underset{\substack{i \in N \\ A_i \geq A_{i+1}}}{U} A_i.$$

QIMEA is described as 4 types as follows: $\left\{ Qn, VQ, Ms, Rs \right\}$, where Qn is the queen; VQ is virgin queen; Ms is males; Rs is rest of the Myrmicinae population.

Graded population in view of that to their function in the colony is defined as

$$A_{\downarrow} = \left\{ \bigcup_{\substack{h=1 \\ Qn_h \geq Qn_{h+1}}}^{J} Qn_h, \; \bigcup_{\substack{j=j+1 \\ VQ_j \geq VQ_{j+1}}}^{K} VQ_j, \; \bigcup_{\substack{k=k+1 \\ Ms_k \geq Ms_{k+1}}}^{L} Ms_k, \; \bigcup_{\substack{l=l+1 \\ Rs_l \geq Rs_{l+1}}}^{N} Rs_l, \; \bigcup_{\substack{i=1 \\ f_l \geq f_{l+1}}}^{N} f_i \right\},$$

$$A_{\downarrow} = \left\{ Qn_h^J, VQ_j^k, Ms_k^l, Rs_l^N, f_i^N \right\}.$$

Quantum computing [29] use strut note: $|\varphi = \alpha|0 + \beta|1, \; |e|^2 + |f|^2 = 1,$

$$\text{Quantum rotation} - U(\theta) = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}, \;\; q_j^t = \left(\begin{array}{c|cc} \alpha_1^t & \alpha_2^t & \alpha_m^t \\ \beta_1^t & \beta_2^t & \beta_m^t \end{array} \right),$$

$$\left| \varnothing_{q_j^t} = \sum_{k=1}^{2^m} \frac{1}{\sqrt{2^m}} \right| s_k.$$

Quantum-inspired Myrmicinae evolutionary algorithm:

a. Start
b. Parameters are initialized
c. Preliminary population are engendered
d. Each individual of the preliminary population has been checked
e. In deterministic solution set fitness assessment has been conducted
f. Most excellent individual and its corresponding fitness have been documented

g. Stop condition of computation procedure has been prepared and verified
h. Each individual of population has been checked again to about the deterministic solution
i. Fitness of each deterministic solution has been computed
j. By means of quantum revolution gate, specific set has been rationalized: $(\alpha_i, \beta_i)^t$ and $(\alpha_i^t, \beta_i^t)^t$ are the possibility of breadth in number of i quantum revolution gate beforehand and after apprising, then $\begin{pmatrix} \alpha_i^t \\ \beta_i^t \end{pmatrix} = U(\theta) \begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix}$
k. Optimal individual and the analogous fitness value has been recorded
l. The computation procedure should stop or not is verified by going back step "e".
m. End

Herpestes optimization algorithm. Herpestes are the nominal genus of mongoose family and found widespread in African countries. Initialized rudiments are constantly measured to be adults on one occasion the HO algorithm takes dissimilar stratagem for adults and remaining Herpestes: $y(k) = y(k-1) + \text{running rate}\left[y_{rand1}(k-1) - y(k-1)\right]$, $y_{rand1} \in [0,1]$. If the parent (mother) is living then the movement mathematically defined as follows:

$$y(k) = y(k-1) + \text{running rate}\, rand_3 \left[y_{parent_{mother}} - y(k-1)\right] + ns,\; ns \in [0,1],$$
$$y(k) = y(k-1) + \text{running rate}\, rand_3 \left[y_{group_{center}} - y(k-1)\right] + ns,\; ns \in [0,1],$$
$$y(k) = y_{parent_{father}} + ns\left[y_{parent_{mother}} - y_{parent_{father}}\right] + ns,\; ns \in [-1,1],$$
$$y(k) = y_{parent_{mother}} + ns\left[y_{parent_{father}} - y_{parent_{mother}}\right] + ns,\; ns \in [-1,1],$$

where ns is a noise signal.

Once the Herpestes population movement, mating and demise are over, the Herpestes group actions or performance is validated. This computation is done as follows:

$$\text{real group}_{performance} = \frac{1 - \left(\text{most excellent fitness}_{group} - \text{fitnes target}_{group}\right)}{\text{most excellent fitness}_{population} - \text{fitnes target}_{group}}.$$

Herpestes optimization algorithm:

a. Start
b. Initialization of population

c. Cluster the Herpestes
d. Movement of parent (father) to premium position
e. Assessment of parent (father)
f. Is parent (mother) available? If *yes* then movement of the new born towards mother
g. Or else it moves towards the center of the group
h. Assessment of new born Herpestes
i. Pick the leading Herpestes
j. Apply mating procedure
k. Completion of life cycle
l. Assessment of cluster quality
m. Is maximum assessment of the function reached? If *yes* then stop or else go to step "c"
n. End

Philander olrogi optimization algorithm. Philander olrogi optimization algorithm is designed based on the actions of Philander olrogi. With reference to most excellent search agent acquired so far, consequently remaining search agents can modernize their location and it defined as follows: $\vec{O} = M\vec{O}_p(y) + N\left(\vec{O}_b(y) - \vec{O}_p(y)\right)$; $M \in [1, 5]$, $N \in [0, 2]$, where $\vec{O}_p(y)$ symbolize the position of Philander olrogi; $\vec{O}_b(y)$ indicate the most excellent optimal solution; M and N are accountable for the exploration and exploitation in the course of the algorithm:

$$M = G - y\left(\frac{G}{\text{iteration}_{\max}}\right), \quad N = 2\ \text{random}(\ ).$$

Then the combating procedure of the Philander olrogi is scientifically defined by

$$\vec{O}_p(y+1) = \left|\vec{O}_b(y) - \vec{O}\right|, \tag{3}$$

where $\vec{O}_p(y+1)$ symbolize the updated position of the Philander olrogi and it modernizes the location or position of other exploring agents with respect to most excellent agent.

Philander olrogi optimization algorithm:

a. Start
b. Initialization of the parameters
c. For each agent compute the fitness value

d. $O_b \leftarrow$ most excellent search agent
e. while $(y <$ maximum iteration$)$ do
f. For every exploring (search) agent do
g. Present exploring (search) agent position rationalised
h. Formula (3)
i. End for
j. Update the parameters: *M*, *N* and *G*
k. Verify — any exploring (search) agent moves beyond the search space; if *yes* — bring back to search space
l. If *no* — then compute the fitness value of each exploring (search) agent
m. Update the O_b when any superior solution available then previous solution
n. $y \leftarrow y+1$
o. End while
p. Return O_b
q. End

Chaotic based Simien Fox optimization algorithm. Chaotic based Simien Fox optimization algorithm is designed based on the natural actions of Simien Fox. Simien Fox population (Z) is poised of N_g groups with N_{sf} Simien Foxes each with $t=0$ in initial phase of iteration within the exploration space demarcated by the interim of $\left[\text{lower bound, upper bound}\right]^D$ and it mathematically defined as:

$$STL_{sf,\,j}^{q,\,t} = \text{lower bound}_j + \text{random}_j\left(\text{upper bound}_j - \text{lower bound}_j\right), \quad (4)$$

where $q=\left[1, 2, \ldots, N_g\right]$; $sf=\left[1, 2, \ldots, N_{sf}\right]$; $j=\left[1, 2, \ldots, \text{dimension}\right]$; $\text{random}_j \in \left[0, 1\right]$.

In the preliminary stage: $STL_{sf,\,j}^{q,\,t} \rightarrow STL_{sf,\,j}^{q,\,0}$. Then the fitness rate is computed as follows: $f_{sf}^{q} = f\left(STL_{sf}^{q,t}\right)$.

In environment, α is designated as possessing preeminent societal circumstance and it defined as

$$\alpha^{q,\,t} = \left\{ STL_{sf}^{q,\,t} \,\middle|\, \arg_{sf=\{1,2,\ldots,N_{sf}\}} \min_{f\left(STL_{sf}^{q,\,t}\right)} \right\}, \quad (5)$$

$$ep_j^{q,\,t} = centre\left(STL_{sf,\,j}^{q,\,t}\right) sf \in \left\{1, 2, \ldots, N_{sf}\right\}, \quad (6)$$

where $j = [1, 2, \ldots, \text{dimension}]$; new-fangled

$$^{*}STL_{sf}^{q,t} = STL_{sf}^{q,t} + R_1\varphi_{ep} + R_2\varphi_{\alpha}. \tag{7}$$

Here $\varphi_{ep} = ep^{q,t} - STL_{srR_1}^{q,t}$, $\varphi_{\alpha} = \alpha^{q,t} - STL_{srR_2}^{q,t}$, $R_1, R_2 \in [0, 1]$.

With reference to new societal circumstances the objective function is computed:

$$^{*}f_{sf}^{q,t} = f\left(^{*}STL_{sf}^{q,t}\right); \tag{8}$$

$$STL_{sf}^{q,t+1} = \begin{cases} ^{*}STL_{sf}^{q,}, & \text{if new-fangled fitness} < f_{sf}^{q,t}, \\ STL_{sf}^{q,t}, & \text{otherwise,} \end{cases} \tag{9}$$

$$W_{help}{}_{j}^{q,t} = \begin{cases} STL_{m_1,j}^{q,t}, & \text{if random}_j < CP_c \text{ or } j = j_1, \\ STL_{m_2,j}^{q,t}, & \text{if random}_j \geq DP_d + CP_c \text{ or } j = j_2, \\ \text{random}_j, & \text{otherwise.} \end{cases} \tag{10}$$

where m_1, m_2 are two picked Simien Foxes; j_1, j_2 are the dimensions; $CP_c = (1 - DP_d)/2$; $DP_d = 1/\text{dimension}$.

Subsequently W_{help} societal circumstance is appraised and the decease canon is applied as follows:

a. Calculate the cluster of poorest altered Simien Foxes has the W_{help} (δ)
b. Calculate the number of Simien Foxes inside the $\delta(\tau)$
c. if $\tau = 1$
d. The W_{help} endures and one Simien Fox in δ deceases
e. otherwise $\tau > 1$
f. The W_{help} endures and primogenital Simien Fox in δ deceases
g. Otherwise
h. W_{help} deceases

Pick the population for subsequent iteration:

$$p_l = 0.0050N_f^2. \tag{11}$$

Simien Foxes years are rationalized in each iteration:

$$years_{sf}^{q,t+1} = years_{sf}^{q,t+1} + 1. \tag{12}$$

In this paper Tinkerbell chaotic map [33, 34] engendering standards are implemented:

$$a_{t+1} = a_t^2 - b_t^2 + ua_t + vb_t, \tag{13}$$

$$b_{t+1} = 2a_t b_t + wa_t + xb_t, \tag{14}$$

where u, v, w, x are non-zero parameters, u = 0.9, v = –0.6, w = 2.0, x = 0.5; $a_t, b_t = 0.1$.

The functional value through linear scaling in Tinkerbell chaotic map [33, 34] is defined as

$$\overset{*}{a}_{t+1} = a_{t+1} - \min a / \max a - \min a. \tag{15}$$

At every iteration, random_1 and random_2 are engendered for every Simien Fox rendering to Gaussian distributions with position factors ρ_{random_1} and ρ_{random_2}:

$$\rho_{\text{random}_1} = (1 - k_{\text{random}}) \rho_{\text{random}_1} + k_{\text{random}} am(\text{Efficacious}_{\text{random}_1}); \tag{16}$$

$$\rho_{\text{random}_2} = (1 - k_{\text{random}}) \rho_{\text{random}_2} + k_{\text{random}} am(\text{Efficacious}_{\text{random}_2}), \tag{17}$$

where *am* is arithmetic mean; $k_{\text{random}} = 0.5$.

Chaotic based Simien Fox optimization algorithm:

a. Start
b. Initialize the parameter values
c. Initialize N_g groups with N_{sf} Simien Foxes each
d. Formula (4)
e. Access the Simien Foxes adaptation
f. While end condition not satisfied do
g. For each *g* group do
h. Outline the α in the group
i. Formula (5)
j. Calculate the groups societal propensity
k. Formula (6)
l. For each Simien Fox do
m. Streamline the Simien Fox societal circumstance
n. Formula (7)
o. Formula (8)
p. Appraise the new-fangled societal circumstance
q. Formula (9)
r. Compute the objective function with reference to Simien Foxes adaptation

s. End for
t. Birth and decease inside the group
u. Formula (10)
v. End for
w. Pick the population for subsequent iteration
x. Formula (11)
y. Groups are reorganized render to DP_d and the connotation probability CP_c
z. Formula (10)
aa. Apply the probabilities using Tinkerbell chaotic map
bb. Formula (12)
cc. Formula (13)
dd. Apprise the factors with reference to societal circumstance in an adaptive procedure
ee. Formula (15)
ff. Formula (16)
gg. Formula (17)
hh. Streamline the years of Simien Fox
ii. Formula (12)
jj. End while
kk. Return the most excellent solution
ll. End

Then the penalty functions involved are $\varphi(Z) = f(Z) + p(Z)$, $p(Z) = \gamma vc \sum_{i=1}^{n} \max\left(0, e_i(Z)\right)^2$, where vc is violated constraints.

The off line inaccuracy (OFLI) is computed by

$$OFLI = \frac{1}{\text{iteration}_{\max}} \sum_{t=1}^{\max} PI_t,$$

where PI is present inaccuracy.

The generalized total calculation of complexity is apportioned as follows:

$$O(ELM),\ O(nd),\ O(n\log n) = O(T(O(s) + O(p))),$$

$$O\left(n^2\right) = O\left(t\left(n^2 + nd\right)\right) = O\left(tn^2 + tnd\right),\ O\left(\text{iteration}_{\max} nd\right).$$

Simulation results and discussion. Projected Extreme learning machine based Phoenicoparrus search optimization algorithm, QIMEA, HO algorithm, PO algorithm and CSFO algorithm are corroborated in IEEE 30 bus system [20].

Table 1 shows the loss appraisal, Table 2 shows the voltage aberration evaluation and Table 3 gives the voltage constancy assessment.

Table 1

Assessment of real power loss

Algorithm	Power loss, MW	Algorithm	Power loss, MW
Hybrid PSOTS [10]	4.5213	B-FS [14]	4.5777
B-TS [10]	4.6862	Hybrid ISFS [14]	4.5142
S-PSO [10]	4.6862	B-FS [16]	4.5275
B-ALO [11]	4.5900	ELMPS	4.4018
Hybrid QOTLBO [12]	4.5594	QIMEA	4.4014
B-TLBO [12]	4.5629	HO	4.5012
S-GA [13]	4.9408	PO	4.5013
B-PSO [13]	4.9239	CSFO	4.4023
Hybrid-AS [13]	4.9059		

Table 2

Comparison of voltage deviancy

Algorithm	Voltage deviancy, PU	Algorithm	Voltage deviancy, PU
Hybrid PSOTVIW [15]	0.1038	B-TLBO [12]	0.0913
Hybrid PSOTVAC [15]	0.2064	B-FS [14]	0.1220
Hybrid PSOTVAC [15]	0.1354	Hybrid ISFS [14]	0.0890
Hybrid PSOCF [15]	0.1287	B-FS [16]	0.0877
Hybrid PGPSO [15]	0.1202	ELMPS	0.0831
Hybrid SWTPSO [15]	0.1614	QIMEA	0.0829
Hybrid PGSWTPSO [15]	0.1539	HO	0.0855
Hybrid MPGPSO [15]	0.0892	PO	0.0851
Hybrid QOTLBO [12]	0.0856	CSFO	0.0831

Table 3

Appraisal of voltage constancy

Algorithm	Voltage constancy L-index, PU	Algorithm	Voltage constancy L-index, PU
Hybrid PSOTVIW [15]	0.1258	B-ABC [11]	0.1161
Hybrid PSOTVAC [15]	0.1499	B-GWO [11]	0.1242
Hybrid PSOTVAC [15]	0.1271	B-BA [11]	0.1252
Hybrid PSOCF [15]	0.1261	B-FS [14]	0.1252
Hybrid PGPSO [15]	0.1264	Hybrid ISFS [14]	0.1245

End of the Table 3

Algorithm	Voltage constancy *L*-index, PU	Algorithm	Voltage constancy *L*-index, PU
Hybrid SWTPSO [15]	0.1488	B-FS [16]	0.1007
Hybrid PGSWTPSO [15]	0.1394	ELMPS	0.1002
Hybrid MPGPSO [15]	0.1241	QIMEA	0.1003
Hybrid QOTLBO [12]	0.1191	HO	0.1003
B-TLBO [12]	0.1180	PO	0.1001
B-ALO [11]	0.1161	CSFO	0.1005

Then the proposed algorithms are substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems deprived of voltage constancy. Loss appraisal is shown in Tables 4 to 6. Table 7 shows the convergence characteristics of the algorithms.

Table 4

Assessment of results

Algorithm	True loss, MW	Ratio of loss diminution	Algorithm	True loss, MW	Ratio of loss diminution
IEEE 14 bus					
Base case [24]	13.550	0	ELMPS	10.034	25.9483
Improved PSO [24]	12.293	9.200	QIMEA	10.040	25.9040
B-PSO [23]	12.315	9.100	HO	10.089	25.5424
B-EP [23]	13.346	1.500	PO	10.094	25.5055
Hybrid SARGA [22]	13.216	2.500	CSFO	10.129	25.2472
IEEE 57 bus system					
Base case [24]	27.80	21.054	ELMPS	0	24.2661
Improved PSO [24]	23.51	21.021	QIMEA	15.400	24.3848
B-PSO [23]	23.86	21.208	HO	14.100	23.7122
Canonical GA [22]	25.24	21.219	PO	9.200	23.6726
Adaptive GA [22]	24.56	21.110	CSFO	11.600	24.0647
IEEE 118 bus system					
Base case [24]	132.8	0	ELMPS	112.009	15.6558
Improved PSO [24]	117.19	11.700	QIMEA	112.27	15.4593
B-PSO [23]	119.34	10.100	HO	112.492	15.2921
B-EPSO [21]	131.99	0.600	PO	112.542	15.2545
B-CLPSO [21]	130.96	1.300	CSFO	112.108	15.5813

Table 5

Appraisal of loss (IEEE 30 bus system)

Algorithm	Actual power loss, MW	Proportion of lessening in power loss	Algorithm	Actual power loss, MW	Proportion of lessening in power loss
Base case [24]	17.5500	0	B-JAYA [25]	17.536	0.07977
Improved PSO [24]	16.0700	8.4000	ELMPS	14.029	20.0626
B PSO [23]	16.2500	7.4000	QIMEA	14.053	19.9259
B-EP [21]	16.3800	6.6000	HO	14.13	19.4800
B-GA [22]	16.0900	8.3000	PO	14.14	19.4300
S-PSO [25]	17.5246	0.14472	CSFO	14.119	19.5498
Improved DEPSO [25]	17.5200	0.17094			

Table 6

Power loss appraisal (IEEE 300 bus system)

Algorithm	True loss, MW	Algorithm	True loss, MW
Adaptive GA [32]	646.299800	QIMEA	625.107903
Faster EA[32]	650.602700	HO	625.108254
B-CSO [31]	635.894200	PO	625.109981
ELMPS	625.109009	CSFO	625.105259

Table 7

Convergence characteristics

Algorithm	Actual loss, (with / without power reliability), MW	Time (with / without power reliability), s	Number of iteration (with / without power reliability)
ELMPS	4.4018 / 14.029	29.42 / 26.34	31 / 28
QIMEA	4.4014 / 14.053	21.20 / 14.35	26 / 22
HO	4.5012 / 14.13	18.81 / 14.89	27 / 24
PO	4.5013 / 14.14	18.89 / 14.92	29 / 27
CSFO	4.4023 / 14.119	30.03 / 28.98	33 / 29

Conclusion. Proposed algorithms reduced the genuine power loss competently. Projected algorithms are corroborated in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained. Extreme learning machine based Phoenicoparrus search optimization algorithm, QIMEA, HO algorithm, PO algorithm and CSFO algorithm creditably condensed the power loss and proportion of actual power loss lessening has been elevated. In PS optimization algorithm Phoenicoparrus assumed that it possesses the maximum nutrition in the *j*-th length. The possibility of perusing the zone for nutrition also upsurges. Then the ELMPS optimization algorithm is designed. Extreme learning machine is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer. Quantum-inspired Myrmicinae evolutionary algorithm design is imitated by the actions of Myrmicinae. In HO algorithm new-fangled position for every Herpestes individual will be considered only when it is superior to the real one. Subsequently second Herpestes group (baby Herpestes) will be in move. In PO algorithm $\vec{O}_b(y)$ symbolize the position of Philander olrogi and $\vec{O}_b(y)$ indicate the most excellent optimal solution. Proposed CSFO algorithm creditably condensed the power loss and proportion of Actual power loss lessening has been elevated. In Simien Fox optimization algorithm, two arbitrary Simien Foxes from dissimilar groups alter their locations with probability p_l. Chaotic sequences are integrated into the SFO optimization algorithm (entitled as CSFO algorithm) and it enhanced the exploration and exploitation. Convergence characteristics show the better performance of the proposed algorithms. Valuation of power loss has been done with other customary reported algorithms.

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