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TRUE POWER LOSS DWINDLING AND STABILITY AUGMENTATION BY EXTREME LEARNING MACHINE BASED HYBRID LEPIDOPTERA-LABIDOGNATHA ALGORITHMS AND RHINOTIA HAEMOPTERA BASED HYBRID CANIS AUREUS GIRNEYS OPTIMIZATION ALGORITHM

L. Kanagasabai gklenin@gmail.com

Prasad V. Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, India

Abstract

In this paper Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha Algorithms and Rhinotia haemoptera based Hybrid Canis aureus and Girneys optimization algorithm has been applied for solving the power loss lessening problem. In Lepidoptera algorithm Location and stage are rationalized in all iteration. The location modernizing procedure is sustained iteratively up until the end norm is satisfied. And in Labidognatha algorithm every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. At its current location it creates vibration when Labidognatha moves to a novel position. In this paper Extreme Learning Machine based Hybrid Lepidoptera and Labidognatha Algorithms is designed to solve the problem. Then in this paper Rhinotia haemoptera based hybrid Canis aureus and Girneys optimization algorithm is modelled for solving the problem. In Canis aureus optimization algorithm deeds of the Canis aureus are used to formulate the algorithm. Through stalking, sneaking and jumping on prey, it hunts. Canis aureus optimization algorithm algorithm imitates the behaviour of Canis aureus as Discover and Stalk segment. Girneys algorithm imitate the deeds of the Girneys have been imitated to formulate the algorithm. Dominant male run the subgroups on the periphery of the central group and communicates

Keywords

Optimal reactive power, transmission loss, extreme learning machine, Lepidoptera, Labidognatha, Rhinotia haemoptera, Canis aureus, Girneys

messages between the peripheral males and the central. In the projected Rhinotia haemoptera based hybrid Canis aureus and Girneys optimization algorithm Portent Canis aureus will control the quarry expanse by the complete pragmatic from earlobes. This exploit is very alike to the doings of Rhinotia haemoptera drive. Then a modernizing strategy which grounded on the cosine function is used to control the process of the algorithm for evading the local optima. Then Girneys movement are included in the hybridized algorithm. Legitimacy of the Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms and Rhinotia haemoptera based hybrid Canis aureus and Girneys optimization algorithm is substantiated in IEEE 30 bus system (with and devoid of *L*-index). Actual power loss lessening is reached. Proportion of actual power loss lessening is augmented

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Introduction. Optimal reactive power dispatch is deliberated as one of the significant conditions for safe and pecuniary operation of a system. It is attained by appropriate organization of the structure apparatus used to cope up the power flow with the goal of diminishing the true power losses and progress the voltage outline of the structure. 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. Ebeed *et al* [6] did the optimal reactive power dispatch using marine predators algorithm considering the uncertainties in load and wind-solar generation systems. 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 semi-definite 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 *et al* [18] had done dual-weighted kernel extreme learning machine for hyperspectral imagery classification. Lv *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. 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 *et al* [26–28] did development of a design algorithm for the logistics system of product distribution of the mechanical engineering enterprise, did the work on organization of logistic systems of scientific productions, 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. Yet many approaches failed to reach the global optimal solution. In this paper, Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms (ELMLLA) and Rhinotia haemoptera based Hybrid Canis aureus and Girneys (RCG) optimization algorithm is applied to solve the factual power loss lessening problem. Lepidoptera algorithm is based on natural deeds of Lepidoptera and they are aquatic or semi-aquatic. Adult Lepidoptera is commonly seen adjacent to bodies of aquatic and are omnivorous all through their life, primarily feeding on petty insects. Usually Lepidoptera are regularly seen close to bodies of aquatic and on the ventral side of Male Lepidoptera have an ovulatory structure an additional abdominal segment will be there. Lepidoptera can function as bio indicators their great quantity designates the profusion of prey in ecosystem. Species prosperity of vascular plants has also been positively related with the classes' richness of Lepidoptera in a positive habitat. Labidognatha algorithm imitates the deeds of Labidognatha and they could not go away from the web as the location of the web stand for infeasible solutions. Every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. Vibration Concentration is in the range of $\left[0, +\infty\right]$. At its current location it creates vibration when Labidognatha moves to a novel position. In Lepidoptera algorithm Location and stage are rationalized in all iterations. Apprising O and ΔO vectors, is by computing the Euclidean distance and pick N of them. The location modernizing procedure is sustained iteratively up until the end norm is satisfied, and in Labidognatha algorithm every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. Vibration Concentration is in the range of $\left[0, +\infty\right]$. At its current location it creates vibration when Labidognatha moves to a novel position. Then in this paper, RCG is proposed for solving the power loss lessening problem. Deeds of the Canis aureus have been modelled to formulate the algorithm. Canis aureus optimization (CO) algorithm imitates the behaviour of Canis aureus into two modes: 1) discover segment; 2) stalk segment. In discover segment the explore behaviour of Canis aureus have four main parameters, which are mentioned as follow: discover memory pools (DMP), search range of the chosen dimension (SRD), produce the dimension to change (PDC) and self location option (SLO). Girneys algorithm (GA) is based on actions of Girneys and it is brown or grey and based on rank in a group, Girneys position themselves. There are two or three oldest and most dominant males which are co-dominant, along with females, their infants, and juveniles in the central male subgroup. They occupying a great diversity of altitudes throughout Central, South, Southeast Asia and have the widest geographic ranges of any non-human primate. The farther to the periphery a subgroup is less dominant than the female. Determining the movements, foraging, and other routines are done by the subgroup. Girneys high-ranking individuals show little tolerance and often show relentless aggression towards non-kin. Sagacity of ELMLLA and RCG is confirmed by corroborated in IEEE 30 bus system (with and devoid of L-index). Factual power loss lessening is achieved. Proportion of factual power loss reduction is amplified.

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

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

$$d = \left[VLG_1, \ldots, VLG_{Ng};\; QC_1, \ldots, QC_{Nc};\;\; T_1, \ldots, T_{NT} \right],$$

$$e = \left[PG_{slack};\; VL_1, \ldots, VL_{NL};\; QG_1, \ldots, QG_{Ng};\; SL_1, \ldots, SL_{NT} \right].$$

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

$$F_1 = P_{\min} = \min\left[\sum_{m}^{NTL} G_m \left[V_i^2 + V_j^2 - 2V_i V_j \cos \text{Ø}_{ij} \right] \right],$$

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

$$F_3 = \min L_{\max}, \quad L_{\max} = \max\left[L_j \right], \;\; j = 1, \ldots, N_{LB},$$

and

$$L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j}, \;\; F_{ji} = -\left[Y_1\right]^1 \left[Y_2\right], \; L_{\max} = \max\left[1 - \left[Y_1\right]^{-1} \left[Y_2\right] \frac{V_i}{V_j} \right].$$

Parity constraints

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

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

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;

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

Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms. In this paper, ELMLLA is designed to solve the problem. Lepidoptera algorithm is based on natural deeds of Lepidoptera and they are aquatic or semi-aquatic. Adult Lepidoptera is commonly seen adjacent to bodies of aquatic and are omnivorous all through their life, primarily feeding on petty insects. Usually, Lepidoptera are regularly seen close to bodies of aquatic and on the ventral side of Male Lepidoptera have an ovulatory structure an additional abdominal segment will be there. Lepidoptera can function as bio indicators their great quantity designates the profusion of prey in ecosystem. Species prosperity of vascular plants has also been positively related with the classes' richness of Lepidoptera in a positive habitat. The performances are methodically modeled as shown below.

The disinterestedness is premeditated by

$$G_i = -\sum_{j=1}^{H} O - O_j. \tag{1}$$

Design of amalgamation is defined as

$$A_i = \frac{\sum_{j=1}^{H} A_j}{H}. \tag{2}$$

Design of unison is described as

$$U_i = \frac{\sum_{j=1}^{H} O_j}{H} - O.$$

Collected stirring in the direction of the sustenance sources is articulated as $C_i = O^+ - O.$ Drive from entrant is calculated as $E_i = O^- + O.$

Drive in the examine space is signposted by the step vector and it defined as

$$\Delta O_{t+1} = \left(tG_i + hH_i + kA_i + bU_i + fE_i \right) + w\Delta O_t. \tag{3}$$

Magnetism grade and step factor is scientifically carved as

$$Z_{next} = z_i + \beta_{ij} \left(z_j z y_i \right) + \alpha \left(R - 0.50 \right). \tag{4}$$

Location vectors are premeditated as

$$O_{t+1} = O_t + \Delta O_{t+1}. \quad (5)$$

Levy flight is encompassed to concentrated the exploration and it scientifically defined as

$$O_{t+1} = O_t + \text{Levy}\left(z\right) O_t. \quad (6)$$

Levy flight is a rank of non-Gaussian arbitrary processes and simple power-law formula $L\left(s\right) \sim \left|s\right|^{-1-\beta}$, where $0 < \beta < 2$ is an index;

$$L\left(s, \gamma, \mu\right) = \begin{cases} \sqrt{\dfrac{\gamma}{2\pi}}, \ \exp\left[-\dfrac{\gamma}{2\left(s-\mu\right)}\right]\dfrac{1}{\left(s-\mu\right)^{3/2}}, \ \text{if } 0 < \mu < s < \infty; \\ 0, \quad \text{if } s \le 0, \end{cases}$$

$$F\left(k\right) = \exp\left[-\alpha\left|k\right|^{\beta}\right], \ 0 < \beta \le 2.$$

In the proposed method, the step sizes are produced using Levy distribution to examine the exploration zone and calculated as

$$s_s\left(t\right) = 0.0010\, s\left(t\right) sL. \quad (7)$$

Solutions of modernized equation of the premium entity is defined as

$$z'_{ij}\left(t+1\right) = z_{ij}\left(t\right) + s\_s\left(t\right) U\left(0,1\right). \quad (8)$$

Location and stage are rationalized in all iteration. Apprising O and ΔO vectors are by computing the Euclidean distance and pick N of them. The location modernizing procedure is sustained iteratively up until the end norm is satisfied:

a. Start
b. Engender the population
c. Steps vectors are initialized
d. Compute the objective function
e. Adjust the nutriment spring and contending factor
f. Calculate and modernize the crucial features
g. (1)
h. (2)
i. Streamline nearby Lepidopteraradius
j. Streamline the drive
k. (3)
l. Modernize the location and step vectors

m. (4)
n. (5)
o. Streamline the exploration and location
p. (6)
q. Step sizes are produced by means of Levy distribution
r. (7)
s. Modernize the solution
t. (8)
u. End if
v. Articulate and control the renewed locations based on the limits of parameters
w. End while
x. End

Labidognatha algorithm imitates the deeds of Labidognatha and they could not go away from the web as the location of the web stand for infeasible solutions. Every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. Vibration concentration is in the range of $[0, +\infty]$. At its current location it creates vibration when Labidognatha moves to a novel position. Concentration value demarcated as

$$I(L_s, L_s, t) = \begin{cases} 1/\left(VC_{\max} - f(L_s)\right) \to \max, \\ 1/\left(f(L_s) - VC_{\min}\right) \to \min. \end{cases}$$

Extreme distance between two points in the examination space indicated as $ED_{\max} = \overline{X} - X_L$. Distance between Labidognatha is calculated as $ED(L_a, L_b) = L_a - L_{bL}$. Vibration diminution for specific distance premeditated as

$$I(L_a, L_b, t) = I(L_a, L_a, t)\exp\left(-\frac{ED(L_a, L_b)}{Ed_{\max} r_a}\right).$$

Vibration diminution over time is calculated as

$$I\left(L_a(t),\ L_a(t), t+1\right) = I(L_a, L_a, t)\, r_a.$$

Labidognatha on the web shift to novel position in iterations and fitness value is computed as $L_s(t+1) = L_s + \left(L_{tar} - L_s\right)\left(1 - R\Delta R\right)$.

Each Labidognatha in population, consequent to the variable walk step, will have miniature possibility to make a decision on not behind its present target and bound away from its prevailing position is described by

$$L_j = \frac{r_j}{\exp\left(Ed\left(L_s, L_{tar}\right) / Ed_{\max}\right)}.$$

Labidognatha produce novel solutions for the succeeding iteration with the mutation procedure, after an assortment procedure is smeared as follows:

$$L_i^{trail} = L_i^{target} + r_i g_i \otimes \left(L_{r1}^{target} - L_{r2}^{target}\right).$$

Binary vector elements are produced by

$$g_{ij} = \begin{cases} 1, \text{ if } R_{ij} < VC; \\ 0 \quad \text{or else.} \end{cases}$$

Succeeding to creation of the trail vector *i*, the position of Labidognatha *i* in the following iteration is calculated by:

$$L_i^{(t+1)} = \begin{cases} L_i^{trail}, \text{ if } f\left(L_i^{trail}\right) < f\left(L_i\right); \\ L_i \text{ otherwise.} \end{cases}$$

The procedure:

a. Start
b. Bounds values are allocated
c. Population of Labidognatha is produced with memory size
d. For each Labidognatha assign the value
e. while stop criteria not met do
f. For each Labidognatha in population do
g. Compute the fitness value
h. Each locations vibration are created
i. End for
j. For each Labidognatha in population do
k. Vibration formed by other Labidognatha is computed
l. Choose the premium vibration
m. Swap the best one to inferior one
n. End if
o. Capricious walk will be applied
p. Capricious number r will be formed from [0, 1]
q. Allocate an arbitrary location
r. End if
s. End

Extreme learning machine (ELM) is pragmatic and learning speed [17–19] of feed-forward neural networks is composed of input, hidden and output layer. Extreme learning machines are feed forward neural networks for classification, regression, clustering, sparse approximation, compression and feature learning with a single layer or multiple layers of hidden nodes, where the parameters of hidden nodes (not just the weights linking inputs to hidden nodes) need not be tuned. These hidden nodes can be arbitrarily allocated and certainly not rationalized (they are arbitrary protuberance but with nonlinear make over), or can be innate from their ancestors devoid of being altered. Almost in all cases, the output weights of hidden nodes are regularly learned in a solo step, which fundamentally amounts to learning a linear model.

For N

$$\left(z_i, OW_i\right);\ z=\left[z_{i1}, z_{i2}, \ldots, z_{idn}\right]^{OW} \in SR^{dn},$$

$$OW_i=\left[OW_{i1}, OW_{i2}, \ldots, OW_{idn}\right]^{OW} \in SR^{dn},$$

$$\sum_{i=1}^{N} \beta_i mn\left(\omega_i z_j+a_i\right)=OW_j, \quad j=1,2,\ldots,N.$$

$$\text{Output matrix}\left(QM\right)\text{Output weight}\left(\beta\right)=OW,$$

$$QM\left(z_1,\ldots,z_L;\omega_1,\ldots,\omega_L;a_1,\ldots,a_l\right)= \\ =\begin{bmatrix} mn\left(\omega_1 z_1+a_1\right) & \ldots & mn\left(\omega_L z_1+a_L\right) \\ \vdots & \ddots & \vdots \\ mn\left(\omega_1 z_N+a_1\right) & \ldots & mn\left(\omega_L z_N+a_L\right) \end{bmatrix}, \tag{9}$$

$$\beta=QM^{-1}OW. \tag{10}$$

Step by step ELM procedure is defined as:

a. Start
b. Input the parameters
c. Test and eraining sets are formed from the common information
d. With orientation to the "training set" of data — calculate the rate of QM
y. (9)
e. Calculate the rate of weight (output)
z. (10)
f. With orientation to the "test set" of data — calculate the rate of QM
aa. (9)
g. Calculate the actual value by β and QM
h. Compute the error rate

i. Assessment of actual value with probable value
j. Return the error rate
k. End

Extreme Learning Machine based Hybrid Lepidoptera and Labidognatha Algorithms. In Lepidoptera algorithm location and stage are rationalized in all iteration. Apprising O and ΔO vectors are by computing the Euclidean distance and pick N of them. The location modernizing procedure is sustained iteratively up until the end norm is satisfied. In Labidognatha algorithm every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. Vibration concentration is in the range of $[0, +\infty]$. At its current location it creates vibration when Labidognatha moves to a novel position. Here ELMLLA is designed to solve the problem. Figure 1 shows the flow chart of ELMLLA:

a. Start
b. Initialize the population in the search space
c. Build the training dataset
d. Based on fitness rate initial population is converted to training dataset
e. With orientation to training dataset ordering (ELM)will be trained
i. Start
ii. Input the parameters
iii. Test and Training sets are formed from the common information
iv. With orientation to the "training set" of data — calculate the rate of QM
bb. (9)
v. Calculate the rate of weight (output)
cc. (10)
vi. With orientation to the "test set" of data — calculate the rate of QM
dd. (9)
vii. Calculate the actual value by β and QM
viii. Compute the error rate
ix. Assessment of actual value with probable value
x. Return the error rate
xi. End
f. Apply Lepidoptera algorithm

Input the NLS value

i. Start
ii. Engender the population
iii. Step vectors are initialized
iv. Compute the objective function
v. Adjust the nutriment spring and contending factor
vi. Calculate and modernize the crucial features
vii. (1)
viii. (2)
ix. Streamline nearby Lepidoptera radius
x. Streamline the drive
ee. (3)
xi. Modernize the location and step vectors
ff. (4)
gg. (5)
xii. Streamline the exploration and location
hh. (6)
xiii. Step sizes are produced by means of levy distribution
ii. (7)
xiv. Modernize the solution
jj. (8)
xv. End if
xvi. Articulate and control the renewed locations based on the limits of parameters
xvii. End while
xviii. End

g. Apply Labidognatha algorithm along with mutation procedure

i. Start
ii. Bounds values are allocated
iii. Population of Labidognatha is produced with memory size
iv. For each Labidognatha assign the value
i. while stop criteria not met do
v. For each Labidognatha in population do
vi. Compute the fitness value
vii. Each locations vibration are created
viii. End for
ix. Streamline the drive
x. Vibration formed by other Labidognatha is computed
xi. Choose the premium vibration
xii. Swap the best one to inferior one

xiii. End if
xiv. Capricious walk will be applied
xv. Capricious number r will be formed from [0, 1]
xvi. Allocate an arbitrary location
xvii. End if
xviii. End

h. Through trained ordering Lepidoptera are categorized

i. Outstanding vibration concentration is observed, which is in the range of $\left[0, \ +\infty\right]$

j. Process ends when sum of valuation surpasses the extreme sum

k. Otherwise

l. For successive generation "N" Lepidoptera are selected by selection of plan operative design

m. End

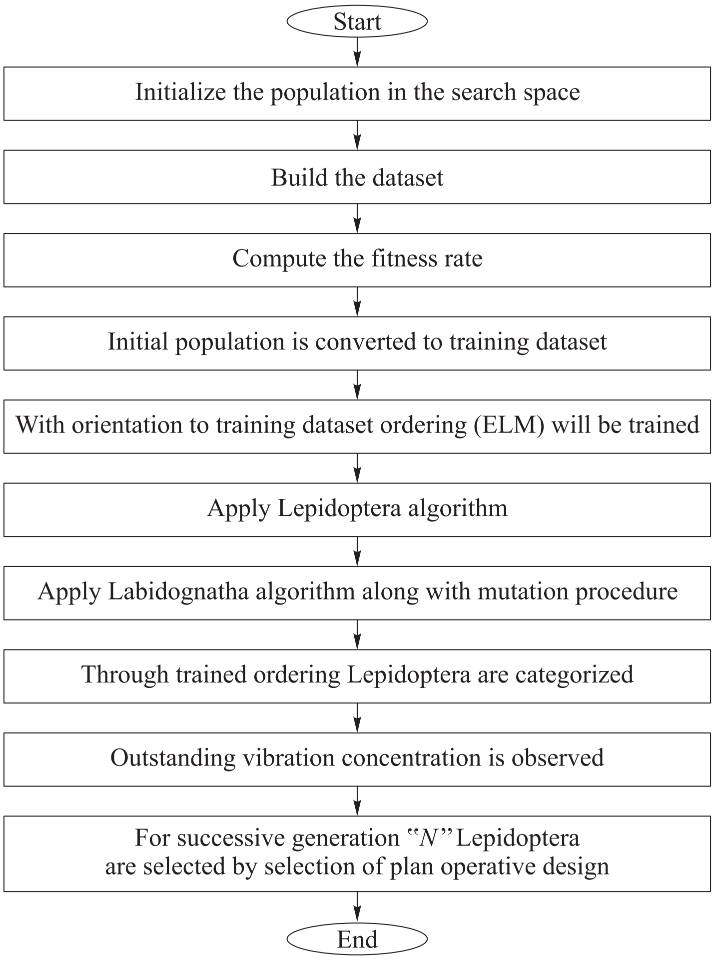


Fig. 1. Flow chart of ELMLLA

Rhinotia haemoptera based Hybrid Canis aureus and Girneys optimization algorithm. Deeds of the Canis aureus have been modelled to formulate the algorithm. In discover segment the explore behaviour of Canis aureus have main parameters: DMP; SRD; PDC; SLO.

The method of explore mode as follow:

i. Engender j copies of the existing location of Canis aureus k, where $j =$ = DMP. When the value of SLO is factual, let j = DMP – 1, conserve the current location as one of the candidates.

ii. As per PDC, for each replica, capriciously adjoin or deduct SRD percentage the present values and regenerate the preceding one.

iii. For all candidate points; fitness values have to be computed.

iv. Fitness values for all are not precisely equal, and then compute the selected possibility of each candidate by selecting the probability of each candidate point is 1.

v. chose the point in arbitrarily mode to shift to from the candidate points, and reinstate the location of Canis aureus k:

$$H_i = \frac{\left|\mathrm{SLO}_i - \mathrm{SLO}_{\max}\right|}{\mathrm{SLO}_{\max} - \mathrm{SLO}_{\min}}. \tag{11}$$

Rendering to the objective of the problem $F_b = F_{\max}$.

In stalk segment Canis aureus desire to sketch the goal and foods. The process of stalk segment can be outlined as follows:

i. Velocity of each dimension is calculated.

ii. Inside the range of maximum limit velocity should be there. If any violation is found, then it has to be brought back to the limit

$$V_{k,d} = V_{k,d} + r_1 c_1 \left(Z_{best,\, d} - Z_{k,d} \right), \tag{12}$$

iii. Renovate the position of Canis aureus k:

$$Z_{k,d} = Z_{k,d} + V_{k,d}. \tag{13}$$

In (12), (13) $Z_{best,\, d}$ is the location of the Canis aureus; $Z_{k,d}$ is the position of Canis aureus k; c_1 is an acceleration coefficient.

In the velocity equation an inertia weight is included. First large inertia value to enhance the global exploration and then inertia value will be abridged to move the stages of local search as follows:

$$W(i) = W_s + \frac{i_{\max} - i}{2 i_{\max}}. \tag{14}$$

Acceleration coefficient formulation is used for modernizing as follows:

$$A(i) = A_s + \frac{i_{\max} - i}{2 i_{\max}}. \tag{15}$$

Rationalized velocity is defined as

$$V_{k,d} = W(d) V_{k,d} + r_1 A(d)\left(Z_{best,d} - Z_{k,d}\right). \tag{16}$$

Modernizing the equations has been done by position data and movement data. Present and regular information of first and subsequent dimensions of both velocity and location are updated by applying a disremembering factor γ:

$$Z_{k,d} = \frac{1}{2}\left[\text{location info} + \text{progression info}\right], \tag{17}$$

$$\text{location info} =$$

$$= Z_{k,d} + \frac{(\gamma Z_{k,d+1}) + (1-\gamma)(Z_{k,d+2})}{2} + \frac{(\gamma Z_{k,d-1}) + (1-\gamma)(Z_{k,d-2})}{2}; \tag{18}$$

$$\text{progression info} =$$

$$= V_{k,d} + \frac{(\gamma V_{k,d+1}) + (1-\gamma)(V_{k,d+2})}{2} + \frac{(\gamma V_{k,d-1}) + (1-\gamma)(V_{k,d-2})}{2}. \tag{19}$$

The procedure:

a. Start
b. Engender *N* Canis aureus
c. Initialize the location, flag and velocity
d. Calculate the fitness value of the each Canis aureus
e. Preeminent Canis aureus (Z_{best}) is stored into memory
f. Rendering to Canis aureus flag, apply Canis aureus to the discover segment
g. (11)
h. Number of Canis aureus are chosen and set them into stalk segment
i. (16)
j. (13)
k. (14)
l. (15)
m. (16)
n. (17)
o. (18)
p. (19)
q. End condition has to be checked, if satisfied, then end the process
r. End

Girneys algorithm (GA) is based on actions of Girneys and it is brown or grey and based on rank in a group, Girneys position themselves. There are two or three oldest and most dominant males which are co-dominant, along with females, their infants, and juveniles in the central male subgroup. They occupying a great diversity of altitudes throughout Central, South, Southeast Asia and have the widest geographic ranges of any non-human primate. The farther to the periphery a subgroup is less dominant than the female. Determining the movements, foraging, and other routines are done by the subgroup. Girneys high-ranking individuals show little tolerance and often show relentless aggression towards non-kin. Deeds of the Girneys has been modelled as follows.

Population size is commenced $z_{iM} \le z_i \le z_{iN}$. Position of each Girneys has been initiated $z_j = \left(z_{j1}, z_{j2}, \ldots, z_{jn}\right)$, $i = 1, 2, \ldots, n$.

Drive of Girneys from primary positions to different position is defined as $\Delta z_j = \left(\Delta z_{j1}, \Delta z_{j2}, \ldots, \Delta z_{jn}\right)$, $i = 1, 2, \ldots, n$,

$$\Delta z_{ij} = \begin{cases} gq\left(g\right) = 0.5; \\ -gT\left(-g\right) = 0.5. \end{cases}$$

Replicated gradient is premeditated by

$$e'_{ij} = \frac{e\left(z_j + \Delta z_j\right) - e\left(z_j - \Delta z_j\right)}{2y_{ij}}, \quad j = 1, 2, \ldots, n,$$

$$e'_{ij} = \left(e'_{j1}\left(z_j\right), e'_{j2}\left(z_j\right), \ldots, e'_{jn}\left(z_j\right)\right),$$

$$y_i = z_{ij} + g\left(c'_{ij}\left(y_j\right)\right), \quad j = 1, 2, \ldots, n.$$

Drive is scientifically defined as

$$z \in \left(X_{ij} - h, X_{ij} + h\right), j = 1, 2, \ldots, n, \quad z_j = X_{ij} + \alpha\left(T_j - z_{ij}\right),$$

$$T_j = \frac{1}{K}\sum_{i=1}^{K} z_{ij}, \quad j = 1, 2, \ldots, n.$$

To poise the exploration and exploitation; info distribution is done by

$$m_{di} = z_{di} + \Phi_{di}\left(z_{di} - z_{ei}\right), \text{ if } m_{di} > z_{di}^{\max} \Rightarrow m_{di} = z_{di}^{\max},$$

$$\text{if } \quad m_{di} < z_{di}^{\max} \Rightarrow m_{di} = z_{di}^{\min}.$$

Procedure:

a. Start

b. Initialize the primary population

c. Compute the fitness value

d. Greedy selection approach used to categorise

e. Fresh positions are engendered

kk. $OP_{new\,ij} = OP_{ij} + \varnothing_1 \left(OP_{kj} - XY_{ij} \right) + \varnothing_2 \left(OP_{rj} - OP_{ij} \right) + F \left(OP_{rj} - OP_{ij} \right)$

f. Based on fitness value greedy selection process is applied between current locations and newly produced location- out of that finest one will be designated

g. Probability value for all the cluster associates will be premeditated by using

ll. $p_i = 0.9 \left(F_i / F_{\max} \right) + 0.09$

h. Modern locations are produced by

mm. $OP_{new\,ij} = OP_{ij} + \varnothing_1 \left(OP_{kj} - XY_{ij} \right) + \varnothing_2 \left(OP_{rj} - OP_{ij} \right) + F \left(OP_{rj} - OP_{ij} \right)$

i. Through greedy selection process the position updating will be done

j. Updating of subgroup members by

nn. $XY_{new\,ij} = XY_{ij} + \varnothing \left(TU_j - XY_{ij} \right) + \varnothing \left(XY_{ij} - MN_{kj} \right)$

k. Adjoin all groups to articulate as a lone cluster

l. Amend the location

m. Up until maximum number of iterations has been touched the process has to be followed

n. End

Rhinotia haemoptera uses its appendages and olfactory pairs to investigate an anonymous atmosphere to discover regions with the sturdiest aroma of sustenance. In every phase, Rhinotia haemoptera mark the whiff with the appendages and then it chooses the progression of the succeeding footstep. Unusually, the Rhinotia haemoptera does not change indiscriminately in certain pathway nonetheless standstills consequently each footstep and customs the intelligence of whiff to enhanced acknowledgment of the independent course beforehand creating the succeeding statement.

In the projected RCG optimization algorithm Portent Canis aureus will control the quarry expanse by the complete pragmatic from earlobes. This exploit is very alike to the doings of Rhinotia haemoptera drive. Then a modernizing strategy which grounded on the cosine function is used to control the process of the CO algorithm for evading the local optima. Then Girneys movement are included in the hybridized algorithm. The advancement completed in the examination performance of Portent Canis aureus α is defined as

$$\vec{D} = \frac{R(Z,1)}{R(Z,1)},$$

where R is random (–1, 1); Z is space length of search.

Grounded on the sound pragmatic by the earlobes of Portent Canis aureus α on the both left-hand and right sides the search is described as

$$\vec{P}_{\alpha}^{left}(n) = \vec{P}_{\alpha}(n) - D(n) \otimes \vec{D}, \quad \vec{P}_{\alpha}^{right}(n) = \vec{P}_{\alpha}(n) + D(n) \otimes \vec{D},$$

$$D(n) = \frac{H(n)}{\text{ratio of}(Hs)}.$$

Then the apprising of step is done by $Hs(n+1) = \rho \otimes Hs(n) + 0.01$.

With orientation to earshot and examination action, the fresh spot of Portent Canis aureus α is described as

$$\vec{P}_{\alpha}^{new}(n) = \vec{P}_{\alpha}(n) + Hs(n) \otimes \vec{D} \otimes S\left(F\left(\vec{P}_{\alpha}^{left}(n)\right) - F\left(\vec{P}_{\alpha}^{right}(n)\right)\right).$$

With orientation to the sound the Portent Canis aureus α will modernize the position by

$$\vec{P}_{\alpha}^{new}(n) = \begin{cases} \vec{P}_{\alpha}^{new}(n) F\left(\vec{P}_{\alpha}^{new}(n) \le \vec{P}_{\alpha}(n)\right); \\ \vec{P}_{\alpha}(n) F\left(\vec{P}_{\alpha}^{new}(n) > \vec{P}_{\alpha}(n)\right). \end{cases}$$

Convergence element $\vec{\varepsilon}$ of the cosine function is described as

$$\vec{\varepsilon} = 2\cos\left(\frac{\pi}{2}\left(\frac{n}{\max\ \text{iteration}}\right)^4\right). \tag{20}$$

Figure 2 shows the flow chart of RCG optimization algorithm.

The procedure:

o. Start
p. Produce the population
q. Parameters are defined
r. Each search agent’s fitness value are calculated
s. Define the pragmatic by the earlobes of Portent Canis aureus
t. while (n < maximum iteration)
u. For each search agent apprise the location
v. End for

w. Rendering to Canis aureus flag, apply Canis aureus to the Discover segment

x. (11)

y. Number of Canis aureus are chosen and set them into stalk segment

z. (12)

aa. (13)

bb. (14)

cc. (15)

dd. (16)

ee. (17)

ff. (18)

gg. (19)

hh. Modernize parameter

ii. (20)

jj. Agent's fitness values are computed

kk. Compute the fitness value

ll. Greedy selection approach used to categorise

mm. Fresh positions are engendered

nn. $OP_{new\,ij} = OP_{ij} + \varnothing_1 \left(OP_{kj} - XY_{ij} \right) + \varnothing_2 \left(OP_{rj} - OP_{ij} \right) + F \left(OP_{rj} - OP_{ij} \right)$

oo. Based on fitness value greedy selection process is applied between current locations and newly produced location — out of that finest one will be designated

pp. Probability value for all the cluster associates will be premeditated by using

qq. $p_i = 0.9 \left(F_i / F_{\max} \right) + 0.09$

rr. Modern locations are produced by

ss. $OP_{new\,ij} = OP_{ij} + \varnothing_1 \left(OP_{kj} - XY_{ij} \right) + \varnothing_2 \left(OP_{rj} - OP_{ij} \right) + F \left(OP_{rj} - OP_{ij} \right)$

tt. Through greedy selection process the position updating will be done

uu. Updating of subgroup members by

vv. $XY_{new\,ij} = XY_{ij} + \varnothing \left(TU_j - XY_{ij} \right) + \varnothing \left(XY_{ij} - MN_{kj} \right)$

ww. Adjoin all groups to articulate as a lone cluster;

xx. Amend the location

yy. Based Rhinotia haemoptera an approach, renovate the way of movement

zz. Update the width

aaa. Reorganization of step length

bbb. Compute the fresh position of Canis aureus

ccc. Streamline the position of Portent Canis aureus
ddd. End for
eee. Update the values
fff. End

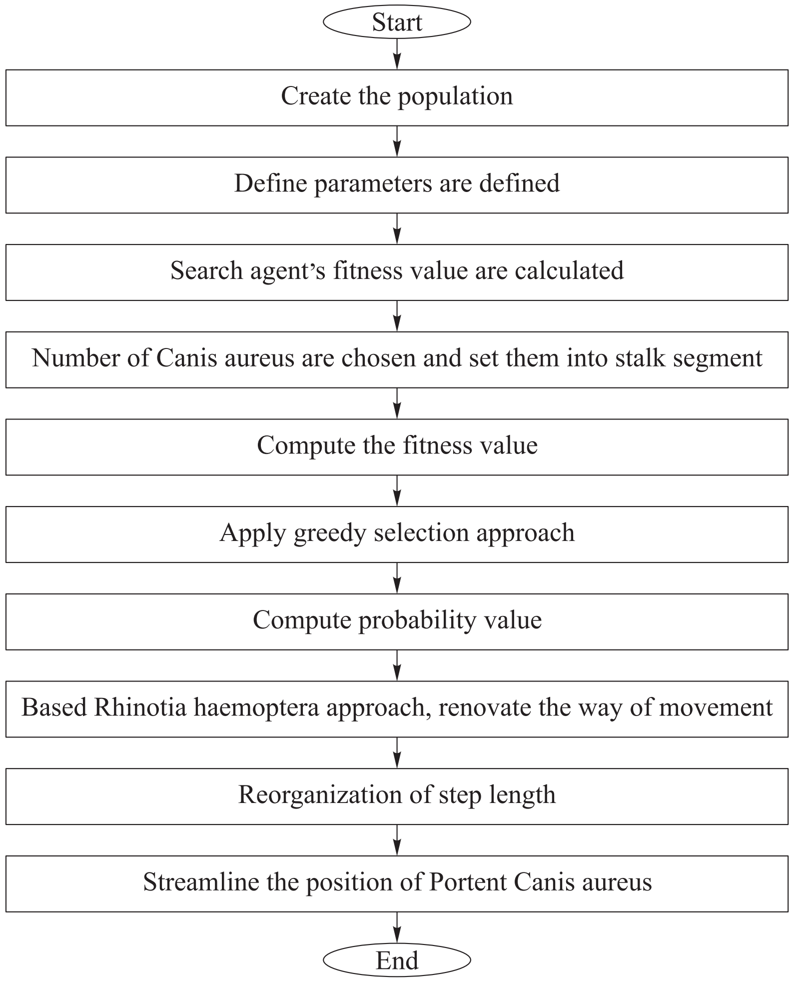


Fig. 2. Flow chart of RCG optimization algorithm

Simulation results. With considering voltage constancy, ELMLLA and RCG optimization algorithm is substantiated in IEEE 30 bus system [20]. Appraisal of loss has been done with PSO, amended PSO, enhanced PSO, widespread learning PSO, Adaptive genetic algorithm, Canonical genetic algorithm (GA), enriched genetic algorithm, Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), Quasi-oppositional teaching learning based (QO-TLBO), Improved stochastic fractal search optimization algorithm (ISFS), Harmony search (HAS), 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. Figure 3 gives graphical appraisal.

Table 1

Assessment of factual power loss lessening

Algorithm	Factual power loss, MW	Algorithm	Factual 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
QO-TLBO [12]	4.5594	Standard FS [16]	4.5275
TLBO [12]	4.5629	ELMLLA	4.4998
Standard GA [13]	4.9408	RCG	4.5001

Table 2

Evaluation of voltage deviation

Algorithm	Voltage deviation, PU	Algorithm	Voltage deviation, PU
Standard PSO-TVIW [15]	0.1038	MPG-PSO [15]	0.0892
Standard PSO-TVAC [15]	0.2064	QO-TLBO [12]	0.0856
Standard PSO-TVAC [15]	0.1354	TLBO [12]	0.0913
Standard PSO-CF [15]	0.1287	Standard FS [14] / Standard FS [16]	0.1220 / 0.0877
PG-PSO [15]	0.1202	ISFS [14]	0.0890
SWT-PSO [15]	0.1614	ELMLLA	0.0830
PGSWT-PSO [15]	0.1539	RCG	0.0838

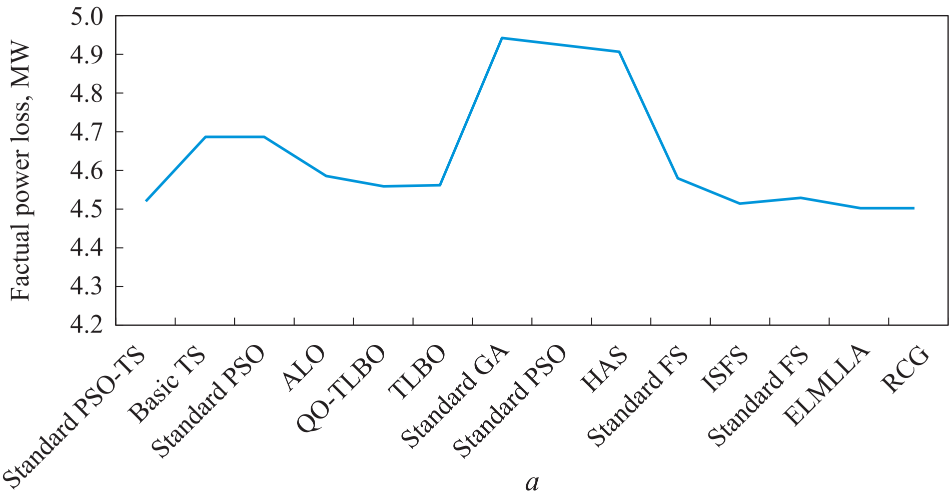
Table 3

Assessment of voltage constancy

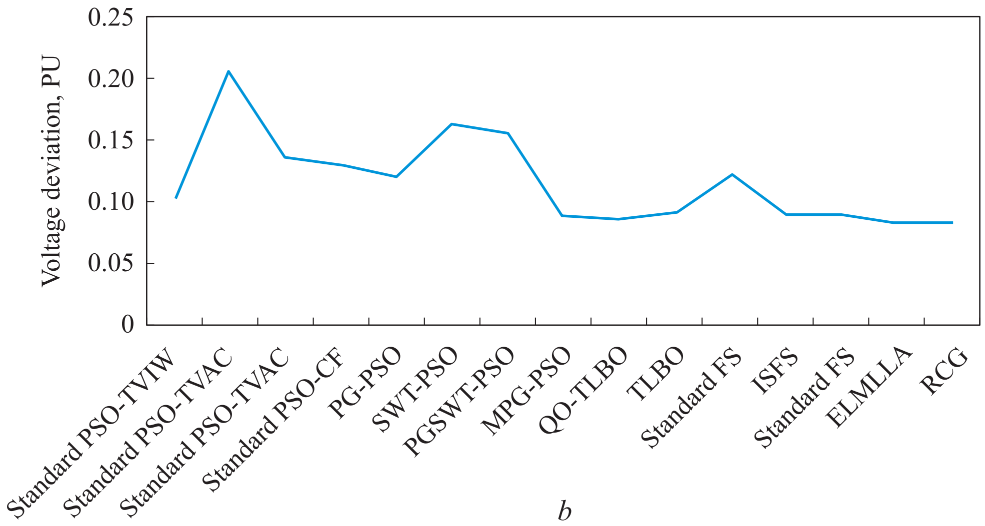
Algorithm	Voltage constancy, PU	Algorithm	Voltage constancy, PU
Standard PSO-TVIW [15]	0.1258	ALO [11]	0.1161
Standard PSO-TVAC [15]	0.1499 / 0.1271	ABC [11]	0.1161
Standard PSO-CF [15]	0.1261	GWO [11]	0.1242

End of the table 3

Algorithm	Voltage constancy, PU	Algorithm	Voltage constancy, PU
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	Standard FS [16]	0.1007
QO-TLBO [12]	0.1191	ELMLLA	0.1002
TLBO [12]	0.1180	RCG	0.1004



a



b

Fig. 3 (beginning). Appraisal of factual power loss (*a*), voltage deviation (*b*)

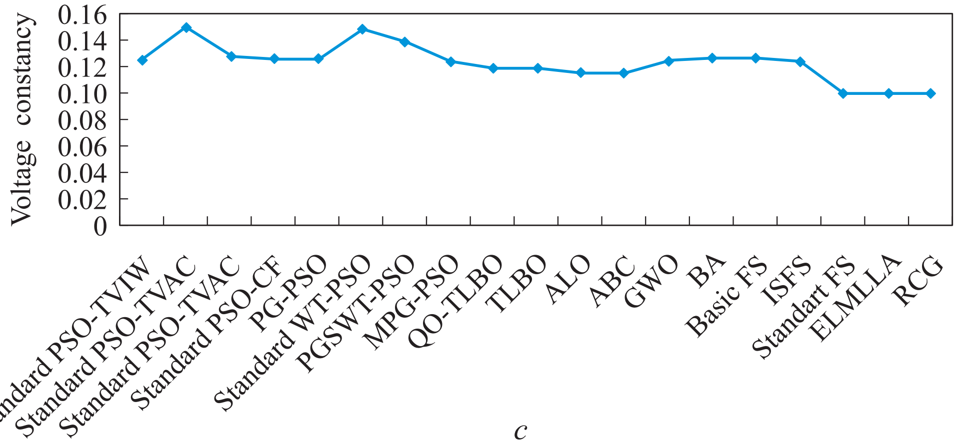


Fig. 3 (ending). Appraisal of voltage constancy (*c*)

Then projected ELMLLA and RCG optimization algorithm is 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 factual power loss.

Table 4

Assessment of true power loss

Algorithm	Factual power loss, MW	Proportion of lessening in power loss
Base case value [24]	17.5500	0
Amended PSO[24]	16.0700	8.40000
Standard PSO [23]	16.2500	7.40000
Standard EP[21]	16.3800	6.60000
Standard GA [22]	16.0900	8.30000
Basic PSO [25]	17.5246	0.14472
DEPSO [25]	17.52	0.17094
JAYA [25]	17.536	0.07977
ELMLLA	13.84	21.1396
RCG	14.05	19.9430

Table 5 shows the convergence characteristics of ELMLLA and RCG optimization algorithm. Figure 5 shows the graphical representation of the characteristics.

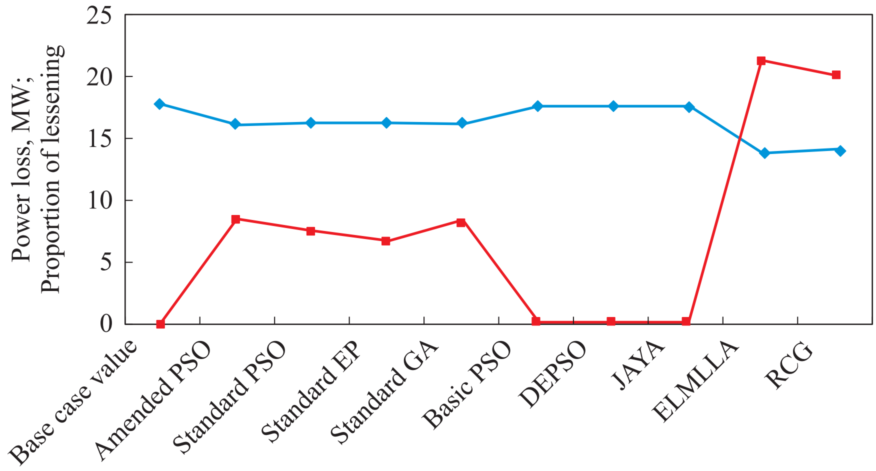


Fig. 4. Appraisal of factual power loss (—◆—),
and proportion of lessening in power loss (—■—)

Table 5

Convergence characteristics

Algorithm	Factual power loss with / without *L*-index, MW	Time with / without *L*-index, s	Number of iterations with / without *L*-index
ELMLLA	4.4998 / 13.84	20.90 / 18.99	33 / 29
RCG	4.5001 / 14.05	19.49 / 18.12	31 / 27

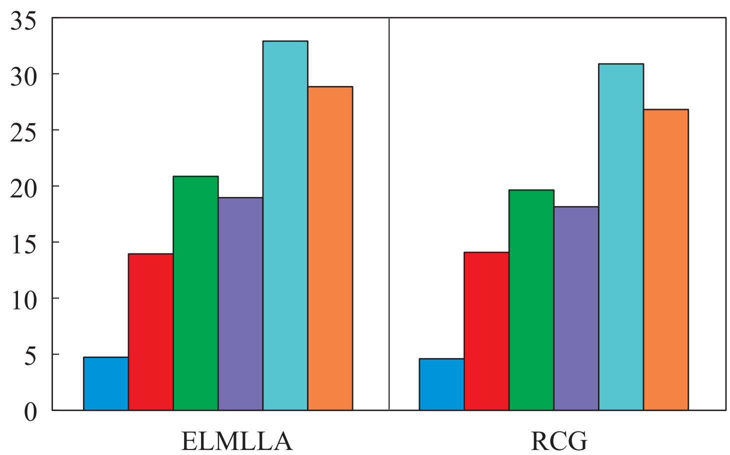


Fig. 5. Convergence characteristics:
factual power loss, MW: with (■) or without (■) *L*-index; time, s: with (■) or without (■) *L*-index; number of iterations with (■) or (■) without *L*-index

Conclusion. Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms and RCG optimization algorithm abridged the factual power loss dexterously. Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms and RCG substantiated in IEEE 30-bus test system with and devoid of voltage constancy. In Lepidoptera algorithm location and stage are rationalized in all iteration. Apprising O and ΔO vectors are by computing the Euclidean distance and pick N of them. The location modernizing procedure is sustained iteratively up until the end norm is satisfied. In Labidognatha algorithm every Labidognatha in population, subsequent to the capricious walk step, will have diminutive probability to make a decision on not following its current target and bound away from its existing position. A vibration is spread over the web when a Labidognatha shifts to a new-fangled location. Every vibration seizes the information of one Labidognatha and other Labidognatha can get the information in receipt of the vibration. Vibration Concentration is in the range of $\left[0, +\infty\right]$. At its current location it creates vibration when Labidognatha moves to a novel position. Then in this paper RGG splendidly solved the power loss lessening problem. Canis aureus optimization algorithm imitates the behaviour of Canis aureus into discover and stalk segments modes. In discover segment the explore behaviour of Canis aureus have main parameters: DMP; SRD; PDC; SLO. Girneys algorithm is based on actions of Girneys and it is brown or grey and based on rank in a group, Girneys position themselves. Determining the movements, foraging, and other routines are done by the subgroup. Girneys high-ranking individuals show little tolerance and often show relentless aggression towards non-kin. In the projected Rhinotia haemoptera based hybrid Canis aureus and Girneys optimization algorithm (RCG) Portent Canis aureus will control the quarry expanse by the complete pragmatic from earlobes. This exploit is very alike to the doings of Rhinotia haemoptera drive. Then a modernizing strategy which grounded on the cosine function is used to control the process of the CO algorithm for evading the local optima. Then Girneys movement are included in the hybridized algorithm. Extreme Learning Machine based Hybrid Lepidoptera-Labidognatha algorithms and RCG optimization algorithm commendably reduced the power loss and proportion of factual power loss lessening has been upgraded. Convergence characteristics show the better performance of the proposed ELMLLA and RCG algorithms. Assessment of power loss has been done with other customary reported algorithms.

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Kanagasabai Lenin — Dr. Sc. (Full), Professor, Department of Electrical and Electronics Engineering, Prasad V. Potluri Siddhartha Institute of Technology (Kanuru, Vijayawada, Andhra Pradesh, 520007 India).

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