Real Power Loss Reduction by Extreme Learning Machine Based Leontodon Algorithm

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Abstract

In this paper Extreme Learning Machine based Leontodon Algorithm (ELMLA) has been applied for solving the Real Power loss reduction problem. Key objectives of this paper are Real power loss reduction, Voltage stability enhancement and voltage deviation minimization. Leontodon Algorithm (LA) technique is an innovative swarm based optimization algorithm. In evolutionary procedure of LA, the eminence of the seeds engendered by Leontodon is rutted, and the outstanding seeds will be reserved and appraised, whereas the deprived seeds are rejected. In order to define whether a seed is tremendous or not, an enhancement of Leontodon algorithm with extreme learning machine (ELMLA) is projected in this paper. Based on fitness values the Leontodon population is segregated into outstanding and deprived Leontodons. Subsequently outstanding and deprived Leontodons are apportioned corresponding labels as +1 if outstanding or −1 if deprived), and it has been considered as a training set, which built on extreme learning machine. Lastly, the design is applied to categorize the Leontodon seeds as excellent or deprived. Only outstanding Leontodon seeds are selected to take part in evolution procedure. Legitimacy of the Extreme Learning Machine based Leontodon Algorithm (ELMLA) is substantiated in IEEE 30 bus system (with and devoid of L-index). Actual Real Power loss reduction is reached. Proportion of actual Real Power loss reduction is augmented.

Keywords Optimal reactive power · Transmission loss · Extreme learning machine · Leontodon

Introduction

At present, the power system network immediately prerequisites to function at complete ability since the demanding venture in power system areas. The optimal reactive power dispatch (ORPD) problem can be deliberated as a vital part of the optimal power flow (OPF) problem. It is a large-scale, nonlinear, discrete, and optimization problem [1] and refers to the reasonable regulation of reactive power through various technologies under the condition of sufficient reactive power, so as

to achieve the optimal distribution of reactive power and the reasonable compensation of reactive power for various loads. The control variables of the ORPD problems include the generators, transformers tapings, shunt reactors, and other reactive power sources. In general, it is perplexing work to find an efficient and convenient method to operate a modern power system, because it must be considered the requirement to recompense the structure for repeatedly altering load demand and provide energy of a high superiority [2]. Consequently, proper distribution and efficient management of reactive power are the major issues which need to be solved urgently in our days [3]. ORPD problems have dealt with various decisions by using a large number of classical algorithms like linear programming [4], interior point methods [5], and Lagrange decomposition method [6]. From the survey about the use of classical

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algorithms, it may be observed that there are obvious drawbacks in these classical algorithms such as insecure convergence, continuity limit, and excessive numerical iterations [7]. Fortunately, as an alternative choice, many researchers have transformed the focus from classical algorithms into computational intelligence-based algorithms which are used to solve the ORPD problems in various power systems [8]. Due to the nonlinear, non-convex, and multimodal nature of the ORPD, most of the methods applied to deal with it are based on computational intelligence-based algorithms [9]. Cuckoo search (CS) algorithm [10], slime mould algorithm (SMA) [11], harmony search algorithm (HSA) [12], particle swarm optimization (PSO) algorithm [13, 14], chaotic krill herd (CKH) algorithm [15], genetic algorithm (GA) [16], immune algorithm (IA) [17], earthworm optimization algorithm (EWA) [18], elephant herding optimization (EHO) [19], moth search (MS) algorithm [20], Harris hawks optimization (HHO) [21], and artificial bee colony (ABC) algorithm [22] have been proposed and used to deal with the ORPD problem. With virtuous tractability, adaptability, and heftiness, they have fascinated countless consideration. Differential evolution (DE) algorithm is one of the most general intelligent optimization algorithms and was first put forward by Storn and Price in 1995 [23]. The foremost feature of DE is its simple structure, the low parameter requirements, and the affluence of use particularly in distributing with cases with nonlinear constraints [24]. Owing to the aforementioned compensations, DE has been extensively used in the power system engineering, such as reactive power dispatching [25–29] and capacitor arrangement [30]. To supplementary progress the convergence speed and optimization consequence of DE in dealing with ORPD, many researchers have made various modifications from different perspectives like regulating scaling factors and crossover factors, mixed with other algorithms and other operations. Awad et al. [31] promulgated an competent DE algorithm for optimal active-reactive power dispatch problems, in which an arithmetic recombination crossover factor and a fresh scaling factor based on Laplace distribution were adapted to augment the performance of the original DE algorithm. Wang et al. [32] proposed a differential evolution algorithm with an adaptive population size adjustment mechanism (SapsDE), which can adaptively determine a more appropriate mutation strategy and its parameter settings according to the previous state at different stages of the evolution process, by this means improving the enactment of DE. Zhang et al. [33] alienated the DE population into manifold groups

firstly and presented a self-adaptive strategy for the control parameters for the purpose of achieving better results. Zhang et al. [34] projected a self-adaptive differential evolution algorithm (JADE), which avoids the obligation for prior knowledge of parameter settings, so it can work well deprived of user interaction. Gao et al. [35] projected an original selection mechanism to augment the overall DE algorithm (NSODE), which selects new individuals from N parents and N children as N better solutions to achieve better optimization results. The goalmouth of adapted DE algorithm in [36] was to increase the convergence speed of the original DE by appraising the adaptive scaling factor, which was able to dynamically exchange information for each generation. Wang et al. [37] proposed a hybrid backtracking search optimization algorithm with differential evolution (HBD), which speeds up function convergence. Mohammad et al. [38] projected a new hybrid algorithm based on the cluster center initialization algorithm (CCIA), bee algorithm (BA), and differential evolution (DE) (called CCIA-BADE-K) and evaluated its performance through standard data sets. Surender [39] presented a hybrid DE and harmony search algorithm for the optimal power flow problem. In [40], monarch butterfly optimization (MBO) is used to extricate the problem of optimal power flow (OPF) for standard IEEE 30- and 118-bus test power systems. Pulluri et al. [41] introduced an enhanced self-adaptive DE with mixed crossover algorithm for dealing with the multi-objective optimal power flow (MO-OPF) problems with conflicting objectives. Although some improved DE algorithms for the ORPD problems have been achieved [31–41], further investigation is still indispensable for the complexity of objectives and constraints. Yet many approaches failed to reach the global optimal solution. In this paper Extreme Learning Machine based Leontodon Algorithm (ELMLA) is applied to solve the Real Power loss reduction problem. Leontodon algorithm is a swarm based algorithm, in which Central Leontodon (CL) and Subordinate Leontodons (SL) will form the Leontodon population, and seeding ways of them are dissimilar. For Central Leontodon (CL) possess one seeding way and it will succour to move out of local optimum. Based on a selection strategy appropriate Leontodons are selected to pass in the subsequent iteration. In the course of the evolution of Leontodon Algorithm (LA), outstanding and deprived Leontodon seeds can be engendered while seeding. The outstanding Leontodon seeds would be reserved, and deprived Leontodon seeds are rejected, this process will diminish the depletion of assessments effectually. In the interim,

the sum of assessments kept can be used to assess more outstanding Leontodon seeds, which can effectually progress the performance of LA. Consequently, categorizing Leontodon seeds is a virtuous choice for refining performance of LA, and the procedure of differentiating whether the Leontodon seed is outstanding or deprived can be considered as a sorting procedure. Input weight and counterbalances of Extreme learning machine (ELM) are engendered arbitrarily, since it is a neural network learning procedure. In the meantime sum of hidden layer nodes must to be fixed. ELM has quicker learning swiftness and enhanced simplification performance. Owing to its gains, the ELM is applied to LA approach to knob the sorting. Grounded on this, an enhancement of evolution procedure of Leontodon algorithm with extreme learning machine (ELMLA) is projected in this paper. In ELMLA, the Leontodon population will be alienated into outstanding (+1) and deprived (-1) grounded on fitness values and this is considered as training dataset. Sequentially the cataloguing design will be constructed by ELM. Lastly, this sorting design is used to categorize the Leontodon seeds. Then the outstanding Leontodon seeds will be reserved and appraised. Sagacity of Extreme Learning Machine based Leontodon Algorithm (ELMLA) is confirmed by corroborated in IEEE 30 bus system (with and devoid of L-index). Proposed Extreme Learning Machine based Leontodon Algorithm (ELMLA) Appraisal of loss has been done with PSO, modified PSO, improved PSO, comprehensive learning PSO, Adaptive genetic algorithm, Canonical genetic algorithm, enhanced 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 proficiently and proportion of the power loss lessening has been enriched. Real Power loss reduction is achieved. Proportion of Real power loss reduction is augmented.

Problem Formulation

Objective function of the problem is mathematically defined in general mode by,

$$\text{Minimization } \tilde{F}(\bar{x}, \bar{y}) \quad (1)$$

Subject to

$$E(\bar{x}, \bar{y}) = 0 \quad (2)$$

$$I(\bar{x}, \bar{y}) = 0 \quad (3)$$

Minimization of the Objective function is the key and it defined by “F”. Both E and I indicate the control and dependent variables. “x” consist of control variables which are reactive power compensators (Q_C), dynamic tap setting of transformers –dynamic (T), level of the voltage in the generation units (V_g).

$$x = [VG_1, \dots, VG_{Ng}; QC_1, \dots, QC_{Nc}; T_1, \dots, T_{N_T}] \quad (4)$$

“y” consist of dependent variables which has slack generator PG_{slack} , level of voltage on transmission lines V_L , generation units reactive power Q_G , apparent power S_L .

$$y = [PG_{slack}; VL_1, \dots, VL_{N_{Load}}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{N_T}] \quad (5)$$

The fitness function (F_1) is defined to reduce the power loss (MW) in the system is written as,

$$F_1 = P_{Min} = \text{Min} \left[\sum_m^{NTL} G_m \left[V_i^2 + V_j^2 - 2 * V_i V_j \cos \theta_{ij} \right] \right] \quad (6)$$

Number of transmission line indicated by “NTL”, conductance of the transmission line between the i^{th} and j^{th} buses, phase angle between buses i and j is indicated by θ_{ij} .

Minimization of Voltage deviation fitness function (F_2) is given by,

$$F_2 = \text{Min} \left[\sum_{i=1}^{N_{LB}} |V_{Lk} - V_{Lk}^{desired}|^2 + \sum_{i=1}^{Ng} |Q_{GK} - Q_{KG}^{Lim}|^2 \right] \quad (7)$$

Load voltage in k^{th} load bus is indicated by V_{Lk} , voltage desired at the k^{th} load bus is denoted by $V_{Lk}^{desired}$, reactive power generated at k^{th} load bus generators is symbolized by Q_{GK} , then the reactive power limitation is given by Q_{KG}^{Lim} , then the number load and generating units are indicated by N_{LB} and Ng .

Then the voltage stability index (L-index) fitness function (OF_3) is given by,

$$F_3 = \text{Min } L_{Max} \quad (8)$$

$$L_{Max} = \text{Max} [L_j]; j = 1; N_{LB} \quad (9)$$

$$\begin{cases} L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j} \\ F_{ji} = -[Y_1]^1 [Y_2] \end{cases} \quad (10)$$

Such that

$$L_{Max} = \text{Max} \left[1 - [Y_1]^{-1} [Y_2] \times \frac{V_i}{V_j} \right] \quad (11)$$

Then the equality constraints are

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \cos[\theta_i - \theta_j] + B_{ij} \sin[\theta_i - \theta_j]] \quad (12)$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \sin[\theta_i - \theta_j] + B_{ij} \cos[\theta_i - \theta_j]] \quad (13)$$

Inequality constraints

$$P_{gslack}^{\min} \leq P_{gslack} \leq P_{gslack}^{\max} \quad (14)$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (15)$$

$$VL_i^{\min} \leq VL_i \leq VL_i^{\max}, i \in N_L \quad (16)$$

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (17)$$

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_C \quad (18)$$

$$|SL_i| \leq S_{L_i}^{\max}, i \in N_{TL} \quad (19)$$

$$VG_i^{\min} \leq VG_i \leq VG_i^{\max}, i \in N_g \quad (20)$$

Then the multi objective fitness (MOF) function has been defined by,

$$MOF = F_1 + x_1 F_2 + y F_3 = F_1 + \left[\sum_{i=1}^{N_L} x_v [VL_i - VL_i^{\min}]^2 + \sum_{i=1}^{N_G} x_g [QG_i - QG_i^{\min}]^2 \right] + x_f F_3 \quad (21)$$

Where real power loss reduction fitness function (F1), Minimization of Voltage deviation fitness function (F2) and voltage stability index (L-index) fitness function (F3) are added to construct the multi objective fitness (MOF) function

$$VL_i^{\min} = \begin{cases} VL_i^{\max}, & VL_i > VL_i^{\max} \\ VL_i^{\min}, & VL_i < VL_i^{\min} \end{cases} \quad (22)$$

$$QG_i^{\min} = \begin{cases} QG_i^{\max}, & QG_i > QG_i^{\max} \\ QG_i^{\min}, & QG_i < QG_i^{\min} \end{cases} \quad (23)$$

Extreme Learning Machine Based Leontodon Algorithm

Leontodon algorithm is a swarm based algorithm, in which Central Leontodon (CL) and Subordinate Leontodons (SL) will form the Leontodon population, and seeding methods of them are divergent. The outstanding Leontodon seeds will be reserved, and deprived Leontodon seeds are rejected, this process will reduce the exhaustion of assessments efficaciously. In pro tem, the sum of assessments kept can be used to evaluate more outstanding Leontodon seeds, which can efficiently progress the performance of Leontodon Algorithm (LA). Therefore, categorizing Leontodon seeds is a righteous choice for purifying performance of LA, and the method of distinguishing whether the Leontodon seed is outstanding or deprived can be considered as a categorization process. Input weight and counterbalances of Extreme learning machine (ELM) are created capriciously, since it is a neural network learning procedure. In the meantime sum of hidden layer nodes must to be fixed. ELM has quicker learning swiftness and enhanced simplification performance. Owing to its gains, the ELM is applied to LA approach to knob the sorting. With reference to this an augmented Leontodon algorithm with extreme learning machine (ELMLA) is projected in this paper. In ELMLA, the Leontodon population will be alienated into outstanding (+1) and deprived (-1) grounded on fitness values and this is considered as training dataset. In LA approach around are three types of operators; standard seeding operator, mutation seeding operator and picking plan operator. The sum of Leontodon seeds engendered is determined and for the Leontodon (Y_i), the sum can be computed as,

Number of Leontodon Seeds (NLS_i)

$$= \begin{cases} NLS_{maximum} \times \frac{Fitness_{maximum} - Fitness(Y_i) + \varepsilon}{Fitness_{maximum} - Fitness_{minimum} + \varepsilon}, \\ NLS_{minimum} \end{cases} \quad (24)$$

In LA approach, the Leontodon with least fitness value is called Central Leontodon (CL). Meant for CL, its seeding radius is animatedly computed with Declining factor (D), Growing Tendency (δ) and Growing factor (G) as follows,

Seeding Raduis ($SR_{CL}(t)$)

$$= \begin{cases} \text{Upper Bound} - \text{Lower Bound} & ; t = 1 \\ SR_{CL}(t) - 1 \times (D); & \delta = 1, t > 1 \\ SR_{CL}(t) - 1 \times (G); & \delta \neq 1, t > 1 \end{cases} \quad (25)$$

$$\text{Growing Tendency } (\delta) = \frac{\text{Fitness}_{CL}(t) + \varepsilon}{\text{Fitness}_{CL}(t-1) + \varepsilon} \quad (26)$$

Seeding radius of the Subordinate Leontodons (SL) is computed by,

$$\text{Seeding Radius } (SR_{SL}(t)) = \begin{cases} \text{Upper Bound} - \text{Lower Bound}, & t = 1 \\ \text{Weight}(\eta) \times SR_{SL}(t-1) + (\|Y_{CL}\|_{\infty} - \|Y_i\|_{\infty}), & \text{otherwise} \end{cases} \quad (27)$$

$$\text{Weight parameter } (\eta) = 1 - \frac{\text{Assessment } (A)}{\text{Assessment } (A)_{\max}} \quad (28)$$

The standard Leontodon seeds are engendered as follows,

- a. Input the NLS value
- b. For $i = 1$ to NLS do
- c. Fix $P = \text{Random}(I, dn)$
- d. For $j = 1$ to dn do
- e. If $j \in P$ then
- f. Model Ψ from Upper Bound $(-1, 1)$
- g. If Y_i is CL then
- h. $LS_i^j = Y_i^j + \Psi \cdot SR_{CL}$
- i. Else
- j. $LS_i^j = Y_i^j + \Psi \cdot SR_{SL}$
- k. End if
- l. If LS_i^j is out of the Bound region then
- m. Value of LS_i^j in Random mode will be picked in [Lower Bound, Upper Bound]
- n. End if
- o. Else
- p. $LS_i^j = Y_i^j$
- q. End if
- r. End for
- s. End for
- t. Return the value of LS_i

The Central Leontodon (CL) has alternative seeding mode, specifically mutation seeding, and engenders mutation Leontodon seeds as shown below,

$$LS_{\text{Mutation}} = Y_{CL} \cdot (1 + \text{Levy} \cdot \text{Random}) \quad (29)$$

Procedure of engendering mutation Leontodon seeds as follows,

- a. Input the LS_{Mutation} value
- b. For $i = 1$ to LS_{Mutation} do
- c. Fix $P = \text{Random}(I, dn)$
- d. For $j = 1$ to dn do
- e. If $j \in P$ then
- f. $LS_{\text{Mutation}}^j = Y_{CL}^j \cdot (1 + \text{Levy}())$
- g. If LS_{Mutation}^j is out of the Bound region then
- h. Value of LS_{Mutation}^j in Random mode will be picked in [Lower Bound, Upper Bound]
- i. End if
- j. End if
- k. End for
- l. End for
- m. Return the value of LS_{Mutation}

In Leontodon Algorithm (LA) the Central Leontodon (CL) should be reserved and enduring Leontodons are chosen by the picking plan probability (PP_i) as follows,

$$PP_i = \frac{|\text{Fitness}(Y_i) - \text{Fitness}_{\text{Average}}|}{\sum_{n=1}^{LSA} \text{Fitness}(Y_n)} \quad (30)$$

Initially, through Standard seeding operator and then Mutation seeding operator engenders the standard and mutation Leontodon seeds and then N Leontodons are selected by picking plan operator. Subsequently introduction of standard seeding operator, mutation seeding operator and picking plan operator, there is a common indulgent of complete outline of LA approach as shown below,

- a. Start
- b. Input the value of N
- c. Engender the population of Leontodon
- d. Compute the fitness value of Leontodon
- e. Engender the standard Leontodon seeds by applying the standard seeding operator procedure
- f. Engender the Mutation Leontodon seeds by applying the Mutation seeding operator procedure
- g. Compute the fitness values of all types of Leontodon seeds
- h. Choose “N” Leontodons by using picking plan operator
- i. Continue the process until stop criterion met
- j. Return the Central Leontodon (CL)

Extreme learning machine (ELM) is applied and learning speed of feed-forward neural networks is poised of input, hidden and output layer.

For N capricious examples (y_i, T_i) ; $y_i = [y_{i1}, y_{i2}, \dots, y_{idn}]^T \in SR^{dn}$, $T_i = [T_{i1}, T_{i2}, \dots, T_{idn}]^T \in SR^{dn}$, (31)

$$\sum_{i=1}^N \beta_i \cdot kn(\omega_i y_j + a_i) = T_j, j = 1, 2, 3, \dots, N \quad (32)$$

$$\text{Output matrix } (Q) \cdot \text{Output weight } (\beta) = T \quad (33)$$

$$Q(y_1, \dots, y_L; \omega_1, \dots, \omega_L; a_1, \dots, a_L) \\ = \begin{bmatrix} kn(\omega_1 y_1 + a_1) & \cdots & kn(\omega_L y_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 y_N + a_1) & \cdots & kn(\omega_L y_N + a_L) \end{bmatrix} \quad (34)$$

$$\beta = Q^{-1} \cdot T \quad (35)$$

The procedure of the Extreme Learning Machine (ELM) is given as below

- Begin
- Input the complete data
- Test and Training set are created from the general data
- With reference to the “training set” of data - compute the value of *Output matrix* (Q)

$$Q(y_1, \dots, y_L; \omega_1, \dots, \omega_L; a_1, \dots, a_L) \\ = \begin{bmatrix} kn(\omega_1 y_1 + a_1) & \cdots & kn(\omega_L y_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 y_N + a_1) & \cdots & kn(\omega_L y_N + a_L) \end{bmatrix}$$

- Compute the value of weight (output)

$$\beta = Q^{-1} \cdot T$$

- With reference to the “test set” of data - compute the value of *Output matrix* (Q)

$$Q(y_1, \dots, y_L; \omega_1, \dots, \omega_L; a_1, \dots, a_L) \\ = \begin{bmatrix} kn(\omega_1 y_1 + a_1) & \cdots & kn(\omega_L y_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 y_N + a_1) & \cdots & kn(\omega_L y_N + a_L) \end{bmatrix}$$

- Compute the real value by β and Q
- Calculation of error value
- Comparison of real value with expected value
- Return the error value
- End

To speed up the performance of the Leontodon Algorithm (LA) in this paper Extreme learning machine (ELM) has been integrated. In the basic procedure of LA approach in each generation “M” Leontodon seeds are engendered, if $kn(kn \leq$

M) Leontodon seeds outstanding (+1) means then $M - kn$ Leontodon seeds is in deprived stage (−1). By utilizing ELM approach into the procedure, if $Y = y_1, y_2, \dots, y_M$ is the set of Leontodon seeds then *first level of kn Leontodon seeds* are in outstanding (+1) and the other Leontodon seeds ($y_{k+1}, y_{k+2}, \dots, y_M$) are in deprived stage (−1). This mode partition will diminish the assessment time, since the deprived (−1) Leontodon seeds will be rejected and fitness value will be calculated only for outstanding (+1) Leontodon seeds. Mainly additional assessment will be utilized for more appraisal of outstanding (+1) Leontodon seeds.

Extreme Learning Machine based Leontodon Algorithm (ELMLA) and fig. 1 shows the flowchart of the algorithm

Simulation Results

With considering L- index (voltage stability), Extreme Learning Machine based Leontodon Algorithm (ELMLA) is substantiated in IEEE 30 bus system [49, 50]. Assessment of real power 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 Real Power loss reduction has been enriched. Predominantly voltage constancy enrichment achieved with minimized voltage deviation. In Table 1 shows the loss appraisal, Table 2 shows the voltage deviation evaluation and Table 3 gives the L-index assessment. Figures 2, 3, 4 gives graphical appraisal.

Then Projected Extreme Learning Machine based Leontodon Algorithm (ELMLA) is corroborated in IEEE 30 bus test system deprived of L- index. Loss appraisal is shown in Tables 4. Figure 5 gives graphical appraisal between the approaches with orientation to Real power loss.

Table 5 shows the convergence characteristics of Extreme Learning Machine based Leontodon Algorithm (ELMLA). Figure 6 shows the graphical representation of the characteristics.

Conclusion

Extreme Learning Machine based Leontodon Algorithm (ELMLA) abridged the Real power loss dexterously. ELMLA substantiated in IEEE 30- bus test system with L-index and devoid of L-index. For Central Leontodon (CL) possess one seeding way and it will succour to move out of local optimum. Based on a selection strategy appropriate Leontodons are selected to pass in the subsequent iteration.

- a. Start
- b. Initialize the population in the exploration space
- c. Constructing the raining dataset
- d. Based on Fitness Preliminary population is transformed to training dataset
- e. With reference to training dataset ordering (Classifier by ELM) will be trained
 - i. Input the complete data
 - ii. Test and Training set are created from the general data
 - iii. With reference to the “training set” of data - compute the value of *Output matrix (Q)*
 - iv.
$$Q(y_1, \dots, y_L; \omega_1, \dots, \omega_L; a_1, \dots, a_L) = \begin{bmatrix} kn(\omega_1 y_1 + a_1) & \dots & kn(\omega_L y_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 y_N + a_1) & \dots & kn(\omega_L y_N + a_L) \end{bmatrix}$$
 - v. Compute the value of weight (output)
 - vi. $\beta = Q^{-1} \cdot T$
 - vii. With reference to the “test set” of data - compute the value of *Output matrix (Q)*
 - viii.
$$Q(y_1, \dots, y_L; \omega_1, \dots, \omega_L; a_1, \dots, a_L) = \begin{bmatrix} kn(\omega_1 y_1 + a_1) & \dots & kn(\omega_L y_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 y_N + a_1) & \dots & kn(\omega_L y_N + a_L) \end{bmatrix}$$
 - ix. Compute the real value by β and Q
 - x. Calculation of error value
 - xi. Comparison of real value with expected value
 - xii. Return the error value
 - xiii. End
- f. Through standard seeding operator regular Leontodon seeds are engendered

Input the NLS value

 - i. *For i = 1 to NLS do*
 - ii. *Fix P = Random(I, dn)*
 - iii. *For j = 1 to dn do*
 - iv. *If j ∈ P then*
 - v. *Model Ψ from Upper Bound (−1,1)*
 - vi. *If Y_i is CL then*
 - vii. $LS_i^j = Y_i^j + \Psi \cdot SR_{CL}$
 - viii. *Else*
 - ix. $LS_i^j = Y_i^j + \Psi \cdot SR_{SL}$
 - x. *End if*
 - xi. *If LS_i^j is out of the Bound region then*
 - xii. *Value of LS_i^j in Random mode will be picked in [Lower Bound, Upper Bound]*
 - xiii. *End if*
 - xiv. *Else*
 - xv. $LS_i^j = Y_i^j$
 - xvi. *End if*
 - xvii. *End for*
 - xviii. *End for*
 - xix. *Return the value of LS_i*
- g. Through Mutation seeding operator mutation Leontodon seeds are engendered
 - i. Input the $LS_{Mutation}$ value
 - ii. *For i = 1 to LS_{Mutation} do*
 - iii. *Fix P = Random(I, dn)*
 - iv. *For j = 1 to dn do*
 - v. *If j ∈ P then*
 - vi. $LS_{Mutation}^j = Y_{CL}^j \cdot (1 + Levy ())$
 - vii. *If LS_{Mutation}^j is out of the Bound region then*
 - viii. *Value of LS_{Mutation}^j in Random mode will be picked in [Lower Bound, Upper Bound]*
 - ix. *End if*
 - x. *End if*
 - xi. *End for*
 - xii. *End for*
 - xiii. *Return the value of LS_{Mutation}*
- h. Through trained ordering (classifier) Leontodon seeds are classified
- i. Outstanding (+1) Leontodon seeds Fitness values are computed
- j. Procedure stops when sum of assessment exceeds the utmost number
- k. Or else
- l. For subsequent generation “N” Leontodons are chosen by picking plan operator pattern
- m. End

Fig. 1 Flow chart of Extreme Learning Machine based Leontodon Algorithm

Table 1 Assessment of Real Power loss reduction

Technique	Real Power loss (MW)
Standard PSO-TS [42]	4.5213
Basic TS [42]	4.6862
Standard PSO [42]	4.6862
ALO [43]	4.5900
QO-TLBO [44]	4.5594
TLBO [44]	4.5629
Standard GA [45]	4.9408
Standard PSO [45]	4.9239
HAS [45]	4.9059
Standard FS [46]	4.5777
IS-FS [46]	4.5142
Standard FS [48]	4.5275
ELMLA	4.5005

Table 2 Evaluation of voltage deviation

Technique	Voltage deviation (PU)
Standard PSO-TVIW [47]	0.1038
Standard PSO-TVAC [47]	0.2064
Standard PSO-TVAC [47]	0.1354
Standard PSO-CF [47]	0.1287
PG-PSO [47]	0.1202
SWT-PSO [47]	0.1614
PGSWT-PSO [47]	0.1539
MPG-PSO [47]	0.0892
QO-TLBO [44]	0.0856
TLBO [44]	0.0913
Standard FS [45]	0.1220
ISFS [45]	0.0890
Standard FS [47]	0.0877
ELMLA	0.0836

To speed up the performance of the Leontodon Algorithm (LA) in this paper Extreme learning machine (ELM) has been integrated. In the basic procedure of LA approach in each generation "M" Leontodon seeds are engendered, if $kn(kn \leq M)$ Leontodon seeds outstanding (+1) means then $M - kn$ Leontodon seeds is in deprived stage (-1). By utilizing ELM approach into the procedure, if $Y = y_1, y_2, \dots, y_M$ is the set of Leontodon seeds then *first level of kn Leontodon seeds* are in outstanding (+1) and the other Leontodon seeds ($y_{k+1}, y_{k+2}, \dots, y_M$) are in deprived stage (-1). This mode partition will diminish the assessment time, since the deprived (-1) Leontodon seeds will be rejected and fitness value will be calculated only for outstanding (+1) Leontodon seeds. Mainly additional assessment will be utilized for more appraisal of outstanding (+1) Leontodon seeds. Therefore categorizing Leontodon seeds is a righteous choice for purifying

Table 3 Assessment of voltage constancy

Technique	Voltage constancy (PU)
Standard PSO-TVIW [47]	0.1258
Standard PSO-TVAC [47]	0.1499
Standard PSO-TVAC [47]	0.1271
Standard PSO-CF [47]	0.1261
PG-PSO [47]	0.1264
Standard WT-PSO [47]	0.1488
PGSWT-PSO [47]	0.1394
MPG-PSO [47]	0.1241
QO-TLBO [44]	0.1191
TLBO [44]	0.1180
ALO [43]	0.1161
ABC [43]	0.1161
GWO [43]	0.1242
BA [43]	0.1252
Basic FS [46]	0.1252
IS-FS [46]	0.1245
Standard FS [48]	0.1007
ELMLA	0.1001

Fig. 2 Appraisal of actual power loss **Fig. 3** Appraisal of Voltage deviation **Fig. 4** Appraisal of voltage constancy

Table 4 Assessment of true power loss

Parameter	Real Power Loss in MW	Percentage of Real Power Loss Reduction
Base case value [53]	17.5500	0.0000
Amended PSO [53]	16.0700	8.40000
Standard PSO [51]	16.2500	7.4000
Standard EP [52]	16.3800	6.60000
Standard GA [16]	16.0900	8.30000
Basic PSO [52]	17.5246	0.14472
DEPSO [54]	17.52	0.17094
JAYA [54]	17.536	0.07977
ELMLA	13.90	20.79

Fig. 5 Appraisal of Real Power Loss **Table 5** Convergence characteristics

IEEE 30 Bus system	Real power Loss in MW(With L-index)	Real power Loss in MW (without L-index)	Time in Sec (with L-index)	Time in sec (without L-index)	Number of iterations (with L-index)	Number of iterations (without L-index)
ELMLA	4.5005	13.90	18.95	15.90	26	21

Fig. 6 Convergence characteristics of ELMLA

performance of LA, and the method of distinguishing whether the Leontodon seed is outstanding or deprived can be considered as a categorization process. Input weight and counterbalances of Extreme learning machine (ELM) are created capriciously, since it is a neural network learning procedure. Extreme Learning Machine based Leontodon Algorithm (ELMLA) commendably reduced the power loss and proportion of Real Power loss reduction has been upgraded. Convergence characteristics show the better performance of the proposed ELMLA algorithm. Assessment of power loss has been done with other customary reported algorithms. Real Power loss reduction achieved by ELMLA is 4.5005 (MW) with considering the Voltage stability index. And without considering Voltage stability index Real Power loss reduction achieved by ELMLA is 13.90 (MW). Percentage of power loss reduction attained is 20.79. In future proposed Extreme Learning Machine based Leontodon Algorithm (ELMLA) can be applied in other areas of power system optimization problem like unit commitment, Economic dispatch problem. Mainly the proposed algorithm can be applied in practical test systems. And in other areas of engineering like image processing, medical field also proposed algorithm can be applied.

Data availability No data available.

Declaration

All ethics are followed

Conflicts of interest No conflict of interest.

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