UDC 519.6 EDN: FIMVMC

REAL POWER LOSS REDUCTION BY EXTREME LEARNING MACHINE BASED DRONGOS SEARCH ALGORITHM

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Abstract

In this paper the Extreme learning machine (ELM) based Drongos search (DS) algorithm — ELMDS algorithm — is applied to solve the power loss lessening problem. Extreme learning machine is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer. Drongos search algorithm is a modern algorithm which is inspired on the elegance performance of Drongos. In expedition to control obscured place a Drongos *j* pursuit Drongos *i*. Formerly Drongos *i* do not sentient of the existence of the added Drongos, as a consequence to the cause of Drongos *j* is to accomplish. And in Fiddling "Drongos" *i* differentiate about the presence of Drongos *j* and it protector its nourishment, Drongos *i* calculatingly take an impulsive way to sentinel its nourishment. This show is replicated by employing an unpredictable evolution. Then care possibility is replaced by a vibrant care possibility for enrichment, which is adapted by the aptness supremacy of every contender solution. Lévy flights are employed as a substitute of unswerving illogical activities to duplicate the dodging performance. In ELMDS algorithm input weight rate and concealed layer inception in ELM are logically optimized by the DS algorithm. Legitimacy of ELMDS algorithm is 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

Keywords

Optimal reactive power, Transmission loss, Extreme Learning Machine, Drongos

Received 04.10.2021
Accepted 27.12.2021

Introduction. Optimal reactive power dispatch is envisaged as one of the remarkable circumstances for safe and fiscal operation of a system. It is consummate by appropriate organization of the edifice 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. Lee *et al.* [1] had done a united approach to optimal real and reactive power dispatch. Dommel *et al.* [2] did optimal power flow solutions. Medani *et al.* [3] solved whale optimization algorithm based optimal reactive power dispatch: A case study of the Algerian power system. Taha *et al.* [4] did optimal reactive power resources sizing for power system operations enhancement based on improved grey wolf optimizer. Sakr *et al.* [5] had done adaptive differential evolution algorithm for efficient reactive power management. Heidari *et al.* [6] applied Gaussian barebones water cycle algorithm for optimal reactive power dispatch in electrical power systems. Keerio *et al.* [7] had done multi-objective optimal reactive power dispatch considering probabilistic load demand along with wind and solar power integration. Roy *et al.* [8] did optimal reactive power dispatch for voltage security using JAYA algorithm. Mugemanyi *et al.* [9] had done optimal reactive power dispatch using chaotic bat algorithm. 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. Reddy [31] solved optimal reactive power scheduling using Cuckoo search algorithm. Reddy [32] did faster evolutionary algorithm based optimal power flow using incremental variables. In this paper Extreme learning machine (ELM) based Drongos search (DS) algorithm — ELMDS algorithm — is applied to solve the real power loss lessening problem. Extreme learning machine is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer. Drongos search algorithm is a modern algorithm which is inspired on the elegance performance of Drongos. In expedition to control obscured place a Drongos *j* pursuit Drongos *i*. Formerly Drongos *i* do not sentient of the existence of the added Drongos, as a consequence to the cause of Drongos *j* is to accomplish. In Fiddling Drongos *i* differentiate about the presence of Drongos *j* and it protector its nourishment, Drongos *i* calculatingly take an impulsive way to sentinel its nourishment. This show is replicated by employing an unpredictable evolution. Each Drongos *i* performance is pronounced by a care possibility *cp*. Consequently, an unpredictable value r_i consistently disseminated between 0 and 1. If r_i is improved than or equivalent to *cp*, show 1 is applied, if not state 2 is designated. Then *cp*, is replaced by a vibrant care possibility *vcp* for enrichment, which is adapted by the aptness supremacy of every contender solution. Lévy flights are employed as a substitute of unswerving illogical activities to duplicate the dodging performance. Accordingly, a novel capricious location $Z_{i,k+1}$ is produced, in addition to the current location $Z_{i,j}$ from calculated Lévy flight Lf. Through Mantegna procedure, the main segment is to evaluate the stage size S_i. In ELMDS algorithm input weight rate and concealed layer inception in ELM are logically optimized by the DS algorithm. Legitimacy of the ELMDS algorithm is 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,

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

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

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 (F_1, F_2, F_3) is designed for power loss (MW) lessening, voltage deviancy, voltage constancy index (L-index) is defined by:

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

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

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

where NTL is number of transmission line; N_{LB}, Ng are number load and generating units; 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; $L_{\max} = \max\left[L_j \right]$, $j = 1, \ldots, N_{LB}$,

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

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

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

Parity constraints:

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

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

Disparity constraints:

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

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

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

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

Multi objective fitness function:

$$MOF = F_1 + r_i F_2 + uF_3 =$$

$$= F_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{\min} \right]^2 + \sum_{i=1}^{Ng} r_g \left[QG_i - QG_i^{\min} \right]^2 \right] + r_f F_3,$$

where 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. Extreme learning machine is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer [17–19]. Remarkably, the learning speed of ELM can be thousands of times quicker than customary feed forward network learning procedures. When equated with orthodox learning algorithms, ELM not only incline to grasp the smallest training error nevertheless it obtains the minimum standard of weights. Extreme learning machine assurances the noble performance, and significantly progresses the learning speed of the forward neural networks, and evades many of the problems of gradient descent training approaches epitomized by BP neural networks, like easiness of being stuck into local optimum, more number of iterations, and so on.

The linking neurons weight matrix of input to hidden layer is demarcated as:

$$Wt = \begin{bmatrix} wt_1^T \\ wt_2^t \\ \vdots \\ wt_l^T \end{bmatrix} = \begin{bmatrix} wt_{11} & \cdots & wt_{1n} \\ \vdots & \ddots & \vdots \\ wt_{L1} & \cdots & wt_{Ln} \end{bmatrix}.$$

Neurons weight matrix of input to hidden layer $(nwt\beta)$ is defined as:

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

Neurons hidden layer bias vector (bvr):

$$bvr = \begin{bmatrix} bvr_1 \\ bvr_2 \\ \vdots \\ bvr_L \end{bmatrix}_{L \times 1}.$$

For N impulsive (u_i, H_i); $u_i = [u_{i1}, u_{i2}, \ldots, u_{idn}]^E \in VU^{dn}$, $H_i = [H_{i1}, H_{i2}, \ldots, H_{idn}]^E \in VU^{dn}$,

$$(H) = \begin{bmatrix} H_1^T \\ H_2^t \\ \vdots \\ H_l^T \end{bmatrix} = \begin{bmatrix} H_{11} & \cdots & H_{1n} \\ \vdots & \ddots & \vdots \\ H_{L1} & \cdots & H_{Ln} \end{bmatrix};$$

$$\sum_{i=1}^{N} nwt\beta_i kn(\omega_i u_j + a_i) = H_j, \; j = 1, \ldots, N;$$

$$(X)(nwt\beta) = H; \tag{1}$$

$$X(u_1, \ldots, u_L; \omega_1, \ldots, \omega_L; a_1, \ldots, a_l) =$$

$$= \begin{bmatrix} kn(\omega_1 u_1 + a_1) & \cdots & kn(\omega_L u_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 u_N + a_1) & \cdots & kn(\omega_L u_N + a_L) \end{bmatrix}; \tag{2}$$

$$nwt\beta = X^{-1}h.$$

Procedure of the ELM is as defined as follows:

a. Begin
b. Input the data
c. Conjoint data test and training sets are created
d. With alignment to the training set — control the amount of (X)
e. (1)
f. Regulate the output rate of weight
g. (2)
h. With alignment to the test set — appraise the rate of (V)
i. (1)

j. Assess the actual rate through $nwt\beta$ and V
k. Computation of error degree
l. Valuation of actual value with possible rate
m. Return the error rate
n. End

Drongos search algorithm. Drongos search algorithm is a modern algorithm which is inspired by elegance performance of Drongos. Magnitude of Drongos is recognized by *N* entities and the position $Z_{i,k}$ of the Drongos *i* in a fixed iteration *k* is demarcated as:

$$Z_{i,k} = \left[z_{i,k}^1, z_{i,k}^2, \ldots, z_{i,k}^n \right],\ i = 1, 2, \ldots, N,\ k = 1, 2, \ldots, \text{max. iter.}$$

Every Drongos is supposed to have the probability of remembering the premium visited position $H_{i,\,k}$ to conceal nourishment up until the contemporary iteration specified as: $H_{i,k} = \left[h_{i,k}^1, h_{i,k}^2, \ldots, h_{i,k}^n \right]$.

Expedition: To control obscured place a Drongos *j* pursuit Drongos *i*. Formerly Drongos *i* do not sentient of the existence of the added Drongos, as a consequence to the cause of Drongos *j* is to accomplish.

Fiddling: Drongos *i* differentiate about the presence of Drongos *j* and it protector its nourishment, Drongos *i* calculatingly take an impulsive way to sentinel its nourishment. This show is replicated by employing an unpredictable evolution.

Each Drongos *i* performance is pronounced by a care possibility *cp*. Consequently, an unpredictable value r_i consistently disseminated between 0 and 1. If r_i is improved than or equivalent to care possibility, show 1 is applied, if not state 2 is designated:

$$Z_{i,\,k+1} = \begin{cases} z_{i,k} + r_i fi_{i,k} \left(H_{i,k} - Z_{i,k} \right) r_i > cp; \\ \quad \text{Rand or else,} \end{cases} \tag{3}$$

where $fi_{i,k}$ is elect the gauge of development from Drongos $Z_{i,k}$ in the way of premium place $H_{i,k}$ of Drongos *j*; the r_i is a whimsical amount with vague dissemination in the sort of [0, 1]. Once the Drongos are personalized, at that moment their position is assessed and memory vector is streamlined:

$$H_{i,\,k+1} = \begin{cases} F\left(Z_{i,k+1}\right)\ F\left(Z_{i,\,k+1}\right) < F\left(H_{i,\,k}\right); \\ \quad H_{i,k} \quad \text{or else.} \end{cases}$$

Then care possibility is replaced by a vibrant care possibility *vcp* for enrichment, which is adapted by the aptness supremacy of every contender solution:

$$vcp_{i,k} = 0.90\frac{F\left(Z_{i,k}\right)}{\omega V} + 0.1. \tag{4}$$

Lévy flights are employed as a substitute of unswerving illogical activities to duplicate the dodging performance. Accordingly, a novel capricious location $Z_{i,k+1}$ is produced, in addition to the current location $Z_{i,j}$ from calculated Lévy flight Lf. Through Mantegna procedure, the main segment is to evaluate the stage size S_i as follows:

$$S_i = \frac{a}{|b|^{1/\beta}},\ a \sim N\left(0, \sigma_a^2\right),\ b \sim N\left(0, \sigma_b^2\right),$$

$$\sigma_a = \left\{\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma\left[(1+\beta)/2\right]\beta^{2(\beta-1)/2}}\right\},\ \sigma_b = 1.$$

Factor Lf is calculated by $\mathrm{Lf} = 0.01 - S_j \in \left(Z_{i,k} - Z^b\right)$.

Novel location $Z_{i,k+1}$ is given by

$$Z_{i,k+1} = Z_{i,k} + \mathrm{Lf}. \tag{5}$$

Crusade and swiftness of the swarm by using particle swarm optimization is integrated in the procedure:

$$vl_i^{t+1} = wv_i^t + c_1 r\left(pb_i - z_i^t\right) + c_2 r\left(g - z_i^t\right); \tag{6}$$

$$z_i^{t+1} = z_i^t + vl_i^{t+1}; \tag{7}$$

$$D_1 r_1 + D_2 r_2 > 0;\ \ \frac{D_1 r_1 + D_2 r_2}{2} - \omega < 0.1;\ \ \omega < 1;\ \ 0 < D_1 + D_2 < 4.0;$$

$$\frac{D_1 + D_2}{2} - 1 < \omega < 1, \text{ then } \omega^{t+1} = K_{Wt}\omega^t.$$

Mutation probability is defined as:

$$M_{pi} = 0.5x\left[\frac{F_{\max} - F_i}{F_{\max} - F_{avg}}\right] \text{ if } F_i \geq F_{avg};$$

$$M_{pi} = \left[\frac{F_{avg} - F_i}{F_{\max} - F_{avg}}\right] \quad \text{if } F_i < F_{avg};$$

$$z_i^{(1,t+1)} = z_i^{(1,t)} + \left(r_i - 0.5\right)\Delta_i,\ \ \Delta_i = 0.5x\left(\max z_i - \min z_i\right);$$

$$\Delta_i = \left(0.03\text{–}0.08\right)x\,avg\ z_i.$$

Afterward the places are rationalized then the mid particle *mp* is included in the population:

$$x_{mp,j}^{t+1} = \frac{\sum_{i=1}^{N-1} z_{i,j}^{t}}{N-1}, \quad j = 1, 2, \ldots, d. \tag{8}$$

By time wavering swiftness fluctuations is organized by

$$Vl_{\max} = \left(1 - \left(\frac{iter}{iter_{\max}}\right)^{g}\right) V_{\max 0}, \quad Vl_{\max 0} = \alpha \left(z_{\max} - z_{\min}\right);$$

$$Pry_i = \frac{F_i}{\sum_{i=1}^{N} F_i}; \tag{9}$$

$$z_{i,j}^{t+1} = \begin{cases} z_{i,j}^{t} \ \text{if } f\left(z_{i,j}^{t}\right) < f\left(z_{i,j}^{t+1}\right); \\ z_{i,j}^{t+1}, \text{ otherwise.} \end{cases} \tag{10}$$

Algorithm

a. Start
b. Initialization of agents
c. Mid particle *mp* is included in the population
d. (8)
e. Particle's location and drive are calculated
f. (6)
g. (7)
h. Quixotically stimulate the Drongos location
i. Memory has been weighed down with orientation to initial position
j. For each place fitness point has been calculated
k. Vibrant care possibility *vcp* is computed
l. (4)
m. Engender the whimsical value r_i for each Drongos i
n. $r_i > vcp$; If "Yes" then compute fresh location
o. (3)
p. If "No" calculate fresh location
q. (5)
r. Prospect of the fresh location has to be set up
s. Fresh locations fitness rate has to be calculated

t. Streamline the memory when development in fitness rate
u. Local operative is smeared
v. (10)
w. (9)
x. Once termination condition is not met then go to step “c”
y. Return the preeminent solution
z. End

ELMDS algorithm. Input weight rate and concealed layer inception in ELM are logically optimized by DS algorithm. Fig. 1 shows the schematic diagram of ELMDS algorithm:

a. Begin
b. Input the data
c. Conjoint data test and training set are created
d. With alignment to the training set — control the amount of (X)
e. (1)
f. Regulate the output rate of weight
g. (2)
h. With alignment to the test set — appraise the rate of (V)
i. (1)
j. Assess the actual rate through $nwt\beta$ and V
k. Calculation of error degree
l. Assessment of real value with probable rate
m. Return the error rate
n. Apply the DS algorithm
   i. Start
   ii. Initialization of agents
   iii. Mid particle *mp* is included in the population
   iv. (8)
   v. Particle’s location and drive are calculated
   vi. (6)
   vii. (7)
   viii. Quixotically stimulate the Drongos location
   ix. Memory has been weighed down with orientation to initial position
   x. For each place fitness point has been calculated
   xi. Vibrant care possibility *vcp* is computed
   xii. (4)
   xiii. Engender the whimsical value r_i for each Drongos i

xiv. $r_i > vcp$; If "Yes" then compute fresh location
xv. (3)
xvi. If "No" calculate fresh location
xvii. (5)
xviii. Prospect of the fresh location has to be set up
xix. Fresh locations fitness rate has to be calculated
xx. Streamline the memory when development in fitness rate
xxi. Local operative is smeared
xxii. (10)
xxiii. (9)
xxiv. Once termination condition is not met then go to step "c"
xxv. Return the preeminent solution
xxvi. End

o. Computing the output error
p. Parameters values are verified
q. Update the data
r. End while
s. Return the optimal solution
t. End

Extreme learning machine process encompasses double steps, training authentication and test segment. The dataset is arbitrarily segregated into dual non-overlapped sets, in order to create the input training authentication matrix and test single. Input matrix is possessing load demand (real and reactive power (P_D), (Q_D)) bus voltage magnitude (V_i). The goal matrix is enclosing power generation (real and reactive power (P_G), (Q_G)) and system losses (real and reactive (P_{ij}), (Q_{ij})). ELM training time 0.0469, training performance is $3.564\mathrm{e}^{-25}$ and testing performance is $8.218\mathrm{e}^{-27}$.

Computation complexit. To compute the fitness value the time is required and the time complication is defined as $O\left(z_1 + N\left(nz_2 + f\left(n\right)\right)\right) = O\left(n + f\left(n\right)\right)$. Then the time required for the iterative update and the time complication is demarcated as $O\left(N\left(nz_3 + f\left(n\right)\right) + z_4 + z_5 + z_6\right) = O\left(n + f\left(n\right)\right)$. The loop fragment time complication is

$$O\left(N\left(nz_3 + f\left(n\right)\right) + z_4 + z_5 + z_6 + N\left(z_2 + z_3\right) + z_1\right) = O\left(n + f\left(n\right)\right).$$

Sequentially the entire time complication is defined as

$$Time\left(n\right) = O\left(n + f\left(n\right)\right) + \left(n + f\left(n\right)\right) = O\left(n + f\left(n\right)\right).$$

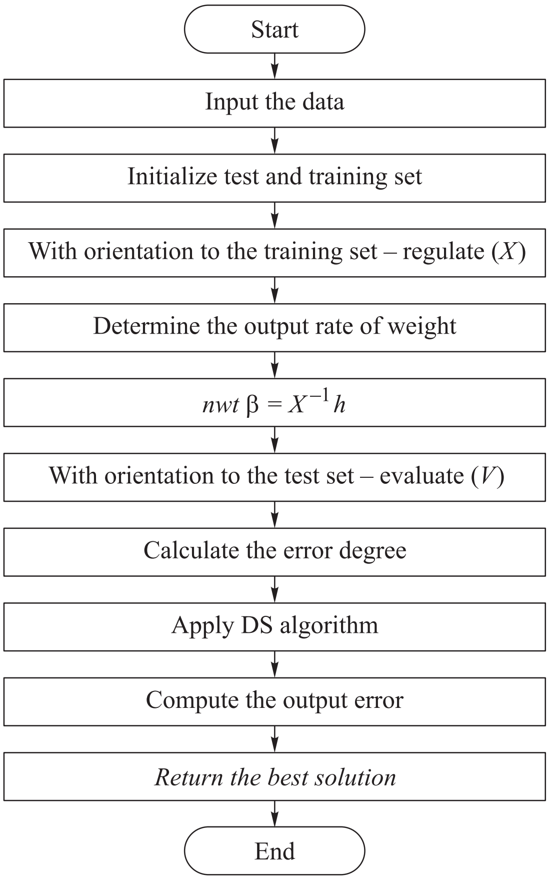


Fig. 1. Schematic diagram of ELMDS algorithm

Simulation results and discussion. Projected ELMDS algorithm is corroborated in IEEE 30 bus system [20]. In Table 1 shows the loss appraisal, Table 2 shows the voltage aberration evaluation and Table 3 gives the voltage constancy assessment. Figures 2, 3 gives the graphical appraisal between the methods. ELMDS abridged the power loss efficiently. Appraisal of loss has been done with particle swarm optimization, adapted particle swarm optimization, enriched particle swarm optimization, comprehensive learning particle swarm optimization, adaptive genetic algorithm, canonical genetic algorithm, enhanced genetic algorithm, hybrid particle swarm optimization — Tabu search, Ant lion approach, quasi-oppositional teaching learning based algorithm, enriched stochastic fractal search optimization algorithm, harmony search, advanced pseudo-gradient search particle swarm optimization and cuckoo search algorithm. Power loss abridged competently and proportion of the power loss lessening has been enhanced. Predominantly voltage constancy augmentation attained with minimized voltage deviancy.

Table 1

Assessment of real power loss

Algorithm	Power loss, MW	Algorithm	Power loss, MW
Hybrid-PSOTS [10]	4.5213	S-GA [13]	4.9408
B-TS [10]	4.6862	B-PSO [13]	4.9239
S-PSO [10]	4.6862	Hybrid-AS [13]	4.9059
B-ALO [11]	4.5900	B-FS [14] / B-FS [16]	4.5777 / 4.5275
Hybrid QOTLBO [12]	4.5594	Hybrid-ISFS [14]	4.5142
B-TLBO [12]	4.5629	ELMDS	4.4019

Table 2

Comparison of voltage deviancy

Algorithm	Voltage deviancy, PU	Algorithm	Voltage deviancy, PU
Hybrid-PSOTVIW [15]	0.1038	Hybrid-QOTLBO [12]	0.0856
Hybrid-PSOTVAC [15]	0.2064	B-TLBO [12]	0.0913
Hybrid-PSOTVAC [15]	0.1354	B-FS [14]	0.1220
Hybrid-PSOCF [15]	0.1287	Hybrid-ISFS [14]	0.0890
Hybrid-PGPSO [15]	0.1202	B-FS [16]	0.0877
Hybrid-SWTPSO [15]	0.1614	CLO	0.0849
Hybrid-PGSWTPSO [15]	0.1539	BO	0.0840
Hybrid-MPGPSO [15]	0.0892	ELMDS	0.0828

Table 3

Appraisal of voltage constancy

Algorithm	Voltage constancy (L-index), PU	Algorithm	Voltage constancy (L-index), PU
Hybrid-PSOTVIW [15]	0.1258	B-TLBO [12]	0.1180
Hybrid-PSOTVAC [15]	0.1499	B-ALO [11]	0.1161
Hybrid-PSOTVAC [15]	0.1271	B-ABC [11]	0.1161
Hybrid-PSOCF [15]	0.1261	B-GWO [11]	0.1242
Hybrid-PGPSO [15]	0.1264	B-BA [11]	0.1252
Hybrid-SWTPSO [15]	0.1488	B-FS [14]	0.1252
Hybrid-PGSWTPSO [15]	0.1394	Hybrid-ISFS [14]	0.1245
Hybrid-MPGPSO [15]	0.1241	B-FS [16]	0.1007
Hybrid-QOTLBO [12]	0.1191	ELMDS	0.1002

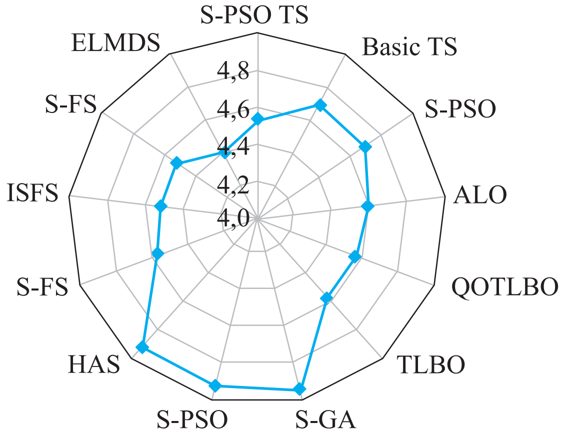
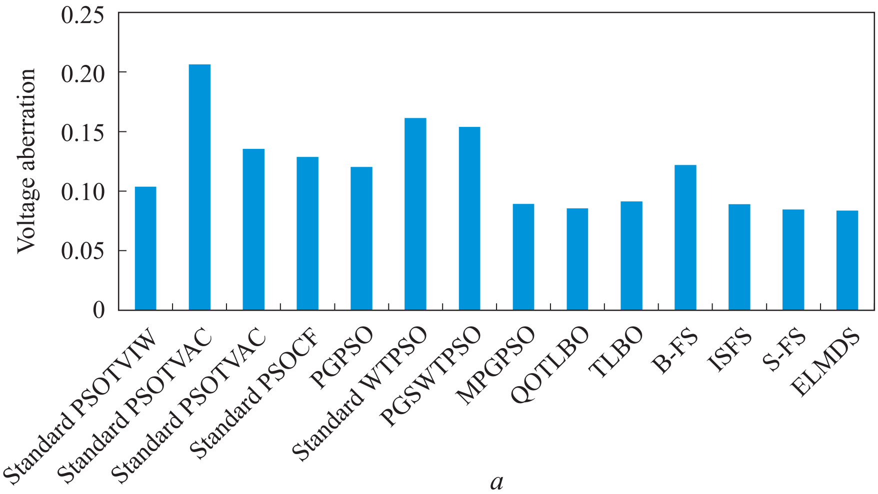
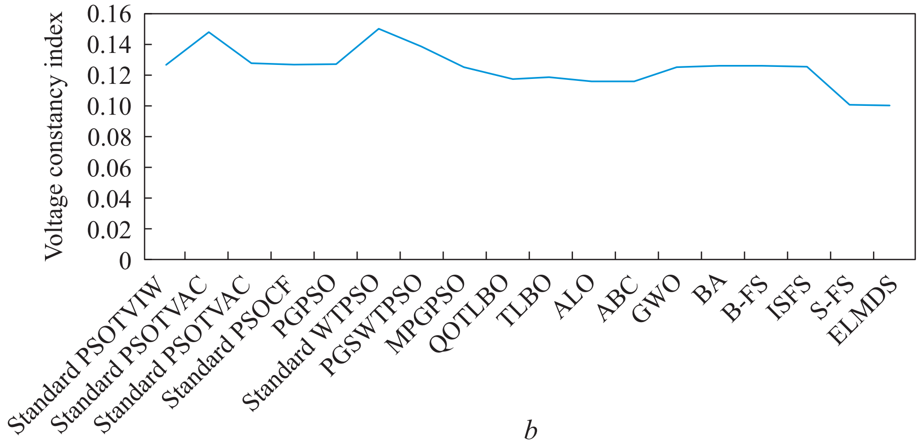


Fig. 2. Assessment of actual power loss, MW



a



b

Fig. 3. Appraisal of voltage aberration (*a*), and assessment of voltage constancy index (*b*)

Then the ELMDS algorithm is substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems deprived of voltage constancy. Loss appraisal is shown in Tables 4 to 8. Figure 4, 5 gives graphical comparison between the approaches with orientation to power loss. Proposed algorithms are compared with adapted particle swarm optimization, particle swarm optimization, evolutionary programming, self-adaptive real coded genetic algorithm, canonical genetic algorithm, adaptive genetic algorithm, enhanced particle swarm optimization, comprehensive learning particle swarm optimization, enhanced genetic algorithm, faster evolutionary algorithm and cuckoo search optimization algorithm.

Table 4

Assessment of results (IEEE 14 bus system)

Algorithm	True loss, MW	Ratio of loss diminution
Base case [24]	13.550	0
Improved PSO [24]	12.293	9.20
B-PSO [23]	12.315	9.10
B-EP [23]	13.346	1.50
Hybrid-SARGA [22]	13.216	2.50
ELMDS	10.069	25.69

Table 5

Appraisal of loss (IEEE 30 bus system)

Algorithm	Actual power loss, MW	Proportion of lessening in power loss
Base case value [24]	17.5500	0
Improved PSO[24]	16.0700	8.40000
B-PSO [23]	16.2500	7.40000
B-EP [21]	16.3800	6.60000
B-GA [22]	16.0900	8.30000
S-PSO [25]	17.5246	0.14472
Improved DEPSO [25]	17.5200	0.17094
B-JAYA [25]	17.5360	0.07977
ELMDS	14.0320	20.0455

Table 6

Assessment of parameters (IEEE 57 bus system)

Algorithm	True loss, MW	Ratio of loss diminution
Base case [24]	27.8	0
Improved PSO [24]	23.51	15.4000
B-PSO [23]	23.86	14.1000
Canonical-GA[22]	25.24	9.2000
Adaptive-GA [22]	24.56	11.6000
ELMDS	21.062	24.2374

Table 7

Assessment of results (IEEE 118 bus system)

Algorithm	True loss, MW	Ratio of loss diminution
Base case [24]	132.8	0
Improved PSO [24]	117.19	11.700
B-PSO [23]	119.34	10.100
B-EPSO [21]	131.99	0.6000
B-CLPSO [21]	130.96	1.3000
ELMDS	112.012	15.6536

Table 8

Power loss appraisal (IEEE 300 bus system)

Algorithm	True loss, MW
Adaptive-GA [32]	646.299800
Faster-EA [32]	650.602700
B-CSO [31]	635.894200
ELMDS	625.106428

Table 9 shows the convergence characteristics of projected ELMDS algorithm for IEEE 30 bus system. In IEEE 30 bus projected ELMDS algorithm has been evaluated as multi objective and single objective mode. Figure 6 shows the graphical representation of the characteristics.

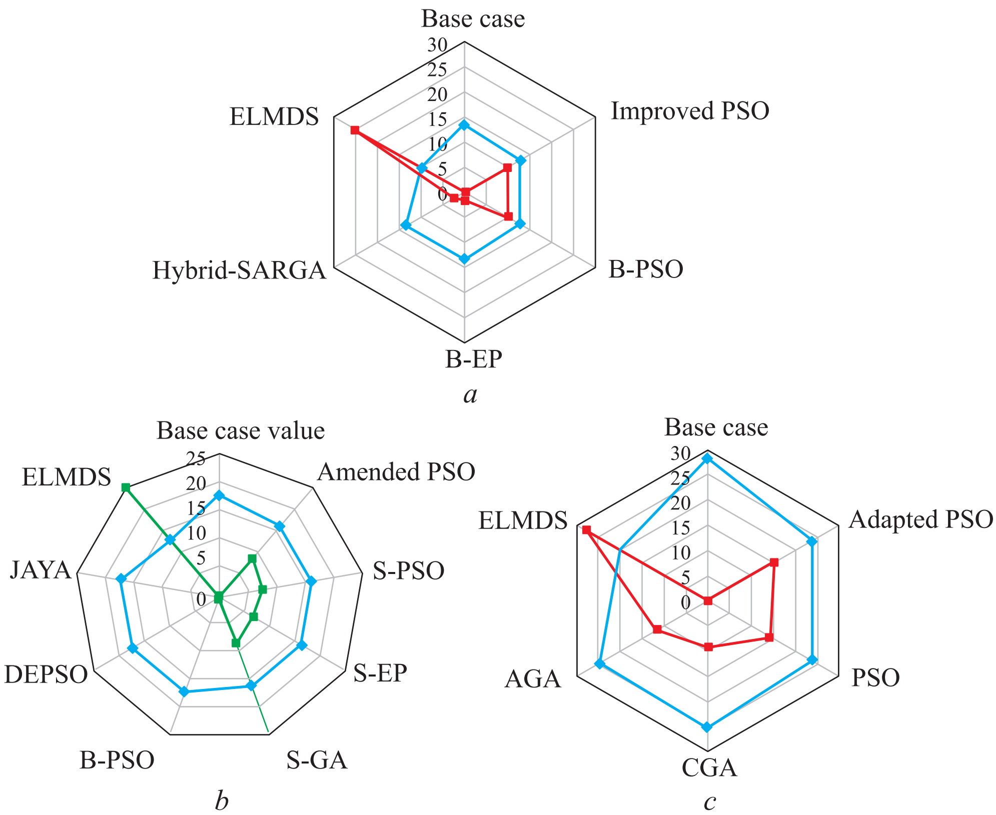


Fig. 4. Power loss appraisal:

a) IEEE 14 bus system; *b*) IEEE 30 bus system; *c*) IEEE 57 bus system; true loss (——), proportion of lessening in power loss (——); ratio of loss diminution (——)

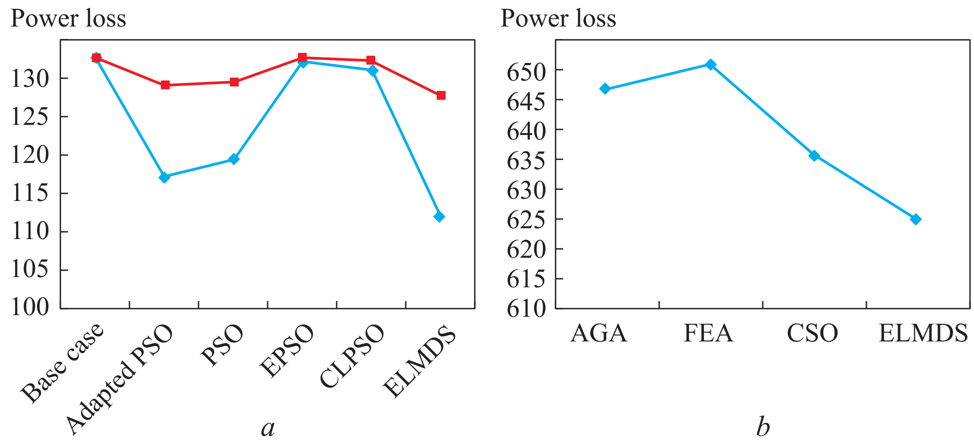


Fig. 5. Power loss appraisal:

a) IEEE 118 bus system; *b*) IEEE 300 bus system; ratio of loss diminution (——), true loss (——)

Table 9

Convergence characteristics of ELMDS algorithm

Actual loss with / without power reliability, MW	Time with / without power reliability, s	Number of iteration with / without power reliability
4.4019 / 14.032	28.29 / 24.98	29 / 20

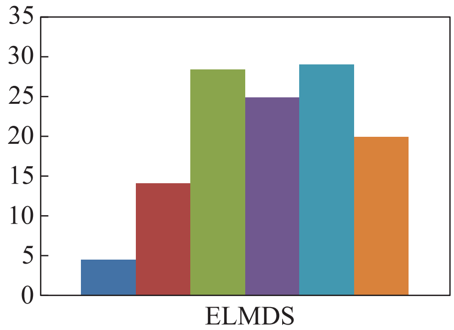


Fig. 6. Convergence characteristics: actual loss with (■) or without (■) voltage constancy; actual loss with (■) or without (■) voltage constancy; number of iteration with (■) or without (■) voltage constancy

Conclusion. ELMDS algorithm reduced the genuine power loss competently. Proposed algorithms is 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. ELMDS algorithm creditably condensed the power loss and proportion of Actual power loss lessening has been elevated. Extreme learning machine is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer. Drongos search algorithm is a modern algorithm which is inspired on the elegance performance of Drongos. In expedition to control obscured place a Drongos *j* pursuit Drongos *i*. Formerly Drongos *i* do not sentient of the existence of the added Drongos, as a consequence to the cause of Drongos *j* is to accomplish. In Fiddling Drongos *i* differentiate about the presence of Drongos *j* and it protector its nourishment, Drongos *i* calculatingly take an impulsive way to sentinel its nourishment. This show is replicated by employing an unpredictable evolution. Each Drongos *i* performance is pronounced by a care possibility. Consequently, an unpredictable value consistently disseminated between 0 and 1. If r_i is improved than or equivalent to care possibility, show 1 is applied, if not state 2 is designated. Then care possibility is replaced by a vibrant care possibility for enrichment, which is adapted by the aptness supremacy of every contender solution. Lévy flights are employed as a substitute of unswerving illogical activities to duplicate the dodging performance. Accordingly, a novel capricious location $Z_{i,k+1}$

is produced, in addition to the current location $Z_{i,j}$ from calculated Lévy flight Lf. Through Mantegna procedure, the main segment is to evaluate the stage size S_i. In ELMDS algorithm input weight rate and concealed layer inception in ELM are logically optimized by the DS algorithm. Convergence characteristics show the better performance of the proposed ELMDS algorithm. Valuation of power loss has been done with other customary reported algorithms.

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Please cite this article as:

Kanagasabai L. Real power loss reduction by extreme learning machine based Drongos search algorithm. *Herald of the Bauman Moscow State Technical University, Series Natural Sciences*, 2024, no. 1 (112), pp. 41–62. EDN: FIMVMC