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Real Power Loss Reduction by Hybridization of Northern Lapwing Mating With Teaching-Learning-Based Optimization and Canis Lupus Dingo with Sine Cosine Algorithm

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Abstract

In this paper at first Hybridization of Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL) is used for solving power loss lessening problem. Northern lapwing mating optimizer (NLM) algorithm is based on the breeding activities of the basal bird. Teaching-learning-based optimization (TLBO) algorithm is grounded on the teaching-learning action in lecture hall. In the instigation of the proposed hybridized algorithm, with large probability value, TLBO operative from side to side imposing exploration competence will increase the solution space. Consequently with minor probability value NLM operative will pursuit in local mode to get the premium solution. Secondly hybridization of Canis lupus dingo algorithm with Sine Cosine Algorithm (HCSC) is done for solving the problem algorithm. Canis lupus dingo algorithm (CLA) emulates the stalking activities of the Canis lupus. Stalking behavior technically replicated and it amplifies the acquaintance about the plausible locality of the prey. Sine Cosine Algorithm (SCA) based on the functions of Sine and Cosine - it stimulates crucial impulsive agent solutions which will swipe externally or innermost style to extent the premium solution. Hybridization of procedures progresses the harmonizing of exploration and exploitation. Both HNLTL and HCSC applied separately and solved the problem effectively. Proposed HNLTL and HCSC are appraised in IEEE 30 bus system with power constancy. Proposed HNLTL and HCSC has been verified in standard IEEE 14, 30, 57,118 and 300 bus test systems deprived of power constancy. Simulation results show the planned HNLTL and HCSC algorithms are condensed the power loss proficiently.

Keywords: optimal reactive power, transmission loss, northern lapwing, teaching, learning, canis lupus dingo, sine cosine

1. Introduction

Power loss lessening problem plays major role in protected and cost-effective operations of system. Power loss lessening problem has been solved by variation of procedures [1-5]. Nonetheless abundant systematic complications are originated while solving the problem due to hodgepodge of restrictions. Evolutionary procedures [6-13] are applied to solve the problem, but the foremost delinquent is voluminous procedures are get jammed in local optimal solution and futile to balance the Exploration & Exploitation throughout the exploration of global solution. Deeb et al. [1] utilised revised linear programming approach. Sun et al [2] applied Newton approach. Estevam et al [3] applied non-linear branch-and-bound algorithm. Chen et al [4] used modified barrier method. Dommel et al [5] did work in Optimal Power Flow Solutions. Singh et al [6] did work on reliability analysis. Das et al [7] used Modified JAYA Algorithm. Singh et al [8] used particle swarm optimization. Wang et al [9] worked in wind farm. Sahli et al [10] used PSO-Tabu. Mouassa et al [11] used lion procedure. Mandal et al [12] applied quasi-oppositional. Khazali et al [13] applied harmony pursuit. Tran et al [14] applied fractal examination process. Polprasert et al [15] applied pseudo-gradient. Thanh et al [16] used Operative Metaheuristic Method. Mirjalili, [17] designed sine cosine algorithm for solving optimization problem. IEEE-test systems [18] give the system data. Ali Nasser Hussain et al [19] applied Modified Particle Swarm Optimization for solving the problem. Surender Reddy [20] applied Cuckoo Search Algorithm. Reddy [21] used faster evolutionary algorithm. Dai et al [22] 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. In this paper, at first Hybridization of Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL) has been applied to solve optimal reactive power problem. Northern lapwing mating optimizer (NLM) algorithm is based on the mating actions of the bird. Female bird genes possess the parthenogenetic and polyandrous. Male bird's genes have monogamous, polygynous and promiscuous. Naturally with one female bird alone a male bird mates then it's defined as Monogamy. Based on the teaching-learning activity in classroom Teaching-learning-based optimization (TLBO) algorithm is modeled. Teacher Phase and Learner Phase are the two prime activities in the TLBO algorithm. In HNLTL P_c is the probability in employing NLM tactic, and probability of $1 - P_c . \mathrm{random}_i(0,1)$. When $\mathrm{random}_i(0,1)$ is superior than or equal to P_c, then NLM operator will execute. Or else TLBO approach will be engaged to engender new-fangled individual. Secondly in this paper hybridization of Canis lupus dingo algorithm with Sine Cosine Algorithm (HCSC) is done for solving optimal reactive power problem. Canis lupus dingo algorithm (CLA) imitates the hunting actions of the Canis lupus. By assuming α, β, δ knowledge about the probable location of the prey will be enhanced. Sine Cosine Algorithm (SCA) produces preliminary arbitrary agent solutions which will swing outwardly or inwardly towards the most excellent solution by using numerical model. In order to avoid to be trapped in local optima Canis lupus dingo algorithm hybridized with sine cosine algorithm (HCSC) through that alpha representative of the Canis lupus dingo is enhanced which based on sine cosine algorithm. Both HNLTL and HCSC applied separately and solved the problem effectively. Proposed HNLTL and HCSC are appraised in IEEE 30 bus system with power constancy. Proposed HNLTL and HCSC has been tested in standard IEEE 14, 30, 57,118 and 300 bus test systems deprived of power constancy. Simulation results show the planned HNLTL and HCSC algorithms are abridged the power loss competently.

2. 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).

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

"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 .

$$y = \begin{bmatrix} PG_{slack}; VL_1, .., VL_{N_{Load}}; QG_1, .., QG_{Ng}; \\ SL_1, .., SL_{N_T} \end{bmatrix} \quad (5)$$

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

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

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 $\emptyset_{ij}$.

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

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

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,

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

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

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

L_{Max} specify the max value

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

Then the equality constraints are

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

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

Where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Inequality constraints

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

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

$$VL_i^{min} \le VL_i \le VL_i^{max}, i \in NL \quad (16)$$

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

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

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

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

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers. The equality constraints are satisfied by running the power flow program. The active power generation (Pgi), generator terminal bus voltages (VGi) and transformer tap settings (tk) are the control variables and they are self-restricted by the optimization algorithm. The active power generation at slack bus (Psl), load bus voltage (Vload) and reactive power generation (QGi) are the state variables and are restricted by adding a quadratic penalty term to the objective function.

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

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

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

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

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

The active power generation (Pgi), generator terminal bus voltages (Vgi) and transformer tap settings (tk) are the control variables and they are self-restricted by the optimization algorithm. The active power generation at slack bus (Psl), load bus voltage (Vload) and reactive power generation (Qgi) are the state variables and are restricted by adding a quadratic penalty term to the objective function.

3. Hybridization of Northern lapwing mating Optimizer Algorithm with Teaching-Learning-Based Optimization Algorithm

Hybridization of Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL) has been designed to solve the power loss lessening problem. Northern lapwing mating optimizer (NLM) algorithm is based on the mating actions of the Northern lapwing bird. Certainly chaste and Bigamy are infatuated by feminine Northern lapwing bird DNAs. Coupledom, Bigamy and myriad are obsessed by Masculine Northern lapwing bird DNAs. Once one feminine Northern lapwing bird breeding with male Northern lapwing bird at that juncture it is recognized as Coupledom. Exclusive Northern lapwing bird from chaste and Bigamy will choose a Northern lapwing bird female for breeding by probabilistic method. At that moment the innovative fledgling Northern lapwing are totalled by,

$$BLB_{new\,young} = BLB + \omega \times \vec{R} \times (BL^i - Bl) \quad (24)$$

if $R_1 >$ mutation influence parameter

$$BLB_{new\,young}(R) = LB(R) - r_2 \times (LB(R) - UB(R)) \quad (25)$$

Bigamy Northern lapwing chose many feminine birds for breeding. At that juncture fresh young ones are calculated as follows,

$$BLB_{new} = BLB + \omega \times \vec{R} \times \left(\sum_{j=1}^{k} \vec{R}_j \times (BLB^i - BLB)\right) \quad (26)$$

if $R_1 >$ mutation influence parameter

$$BLB_{new\,young}(R) = LB(R) - r_2 \times (LB(R) - UB(R)) \quad (27)$$

Every Northern lapwing female bird in probabilistic method will provide fledgling

Northern lapwing bird by means of certainly not the contribution of Northern lapwing male bird and it is through creating a minor transformation in her DNAs while it is apomictic and it described as follows,

for i = 1 : E

if $R_1 >$ mutation influence parameter

$$BLB_{new\ young}(i) = BLB(i) + SR \times (r_2 - r_3) \times BLB(i) \quad (28)$$

Start

a. Initialize the variables
b. Categorize the Northern lapwing birds
c. Recognize the information of the bird species
d. Exclude the vilest Northern lapwing and beget fresh young ones by employing chaotic order
e. Create fresh Northern lapwing bird young ones grounded on types
f. $BLB_{new\ young} = BLB + \omega \times \vec{R} \times (BL^i - Bl)$
g. if $R_1 >$ mutation influence parameter
h. $BLB_{new\ young}(R) = LB(R) - r_2 \times (LB(R) - UB(R))$
i. $BLB_{new} = BLB + \omega \times \vec{R} \times \left(\sum_{j=1}^{k} \vec{R}_j \times (BLB^i - BLB)\right)$
j. if $R_1 >$ mutation influence parameter
a. $BLB_{new\ young}(R) = LB(R) - r_2 \times (LB(R) - UB(R))$
b. for i = 1 : E
c. if $R_1 >$ mutation influence parameter
a. $BLB_{new\ young}(i) = BLB(i) + SR \times (r_2 - r_3) \times BLB(i)$
b. Implement changeover segment
c. Once extreme number of fitness appraisal encountered at that time complete the procedure
d. Otherwise go to step d
e. end

Teaching-learning-based optimization (TLBO) algorithm is grounded on the training - education action in lecture hall [15]. Trainer Segment and Pupil Segment are the two principal actions in the procedure.

In Trainer segment pupils absorb through the trainer and described as follows,

$$TLB_{new} = TLB_i + r \times (TLB_{trainer} - TF \times TLB_{mean}) \quad (29)$$

In Pupil Segment learner amplify his or her acquaintance by means of cluster deliberations

$$\begin{cases} TLB_{new} = TLB_i + r \times (TLB_j - TLB_i) \\ \quad , \text{if } f(TLB_j) < f(TLB_i) \\ y_{new} = y_i + r \times (y_i - y_j), \\ \quad \text{otherwise} \end{cases} \quad (30)$$

In Hybridization of Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL) P_c is the probability in engaging Northern lapwing mating optimizer (NLM) algorithm tactic, and probability of $1 - P_c . random_i(0,1)$. NLM operative will be implemented when $random_i(0,1)$ is greater than or equal to P_c. Otherwise the TLBO method will be betrothed to produce fresh entity with exploration and exploitation is heightened competently. With enormous P_c rate TLBO operative possess virtuous exploration competence which will widen the solution space. At that moment with minor P_c rate premium solution is attained through NLM operative while it pursuits in local method. Fig a shows the Flow chart of Hybridized Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL).

Assortment Probability is defined as,

$$P_c(t) = \sin(\exp(-3t/T)) \quad (31)$$

a. Start
b. Initialize the variables
c. Primary population is created
d. While (end creteria not satisfied)
e. Categorize the Northern lapwing birds
f. Dissolute Northern lapwing are eradicated
g. Fresh Northern lapwing are created by chaotic order
h. Calculate the Probability P_c
i. Every Northern lapwing bird will be in the order of BLB_i
j. if $R_i(0,1) > P_c$
k. Northern lapwing mating optimizer method is employed in the contemporary population
l. $BLB_{new\ young} = BLB + \omega \times \vec{R} \times (BL^i - Bl)$

m. if $R_1 >$ mutation influence parameter

n. $BLB_{new\ young}(R) = LB(R) - r_2 \times (LB(R) - UB(R))$

o. $BLB_{new} = BLB + \omega \times \vec{R} \times \left(\sum_{j=1}^{k} \vec{R}_j \times (BLB^i - BLB)\right)$

p. if $R_1 >$ mutation influence parameter

q. $BLB_{new\ young}(R) = LB(R) - r_2 \times (LB(R) - UB(R))$

r. for $i = 1 : E$

s. if $R_1 >$ mutation influence parameter

t. $BLB_{new\ young}(i) = BLB(i) + SR \times (r_2 - r_3) \times BLB(i)$

u. Otherwise

v. Teaching-learning-based optimization method is practical in current population

w. $TLB_{new} = TLB_i + r \times (TLB_{trainer} - TF \times TLB_{mean})$

x. $\begin{cases} TLB_{new} = TLB_i + r \times (TLB_j - TLB_i), \text{if } f(TLB_j) < f(TLB_i) \\ y_{new} = y_i + r \times (y_i - y_j), \text{otherwise} \end{cases}$

y. $P_c(t) = \sin(\exp(-3t/T))$

z. End If

aa. End For

bb. Evaluate and revolutionize the new-fangled young Northern lapwing

cc. End while

dd. End

ee. Output the premium solution

ff. End

4. Hybridization of Canis lupus dingo algorithm with Sine Cosine Algorithm

Canis lupus dingo algorithm is hybridized with sine cosine algorithm (HCSC) for the power loss lessening problem. Canis lupus dingo algorithm (CLA) imitates the hunting actions of Canis lupus dingo. Canis lupus dingo ringing performance of every representative of the troop is calculated as follows,

$$\overline{HCA} = \left|\overline{U}\overline{O}_p(t) - \overline{O}(t)\right| \tag{32}$$

$$\overline{O}(t+1) = \overline{X}_p(t) - \overline{Q} \cdot \overrightarrow{HCA} \tag{33}$$

$$\vec{Q} = 2\vec{e}.r_1 - \vec{e} \tag{34}$$

$$\vec{U} = 2.r_2 \tag{35}$$

$$\vec{e} = 2 - 2t/t_{max} \tag{36}$$

Stalking behavior systematically replicated by presumptuous that α, β, δ have heightened acquaintance about the plausible position of the victim.

$$\overrightarrow{HCA_\alpha} = \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right| \tag{37}$$

$$\overrightarrow{HCA_\beta} = \left|\overrightarrow{U_2}, \overrightarrow{O_\beta} - \vec{O}\right| \tag{38}$$

$$\overrightarrow{HCA_\gamma} = \left|\overrightarrow{U_3}, \overrightarrow{O_\delta} - \vec{O}\right| \tag{39}$$

$\overrightarrow{O_\alpha}$ - Leading best search agent

$\overrightarrow{O_\beta}$ - Succeeding best search agent

$\overrightarrow{O_\delta}$ - Third search agent

$\overrightarrow{HCA_\alpha}$ specify the Leading best search agent stalking behaviour

$\overrightarrow{HCA_\beta}$ specify the Succeeding best search agent stalking behaviour

$\overrightarrow{HCA_\gamma}$ specify the Third search agent stalking behaviour

$$\vec{e} = 2 - 1 * \left(\frac{2}{\text{max iter}}\right) \tag{40}$$

$$\overrightarrow{HCA_\alpha} = \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right| \tag{41}$$

$$\overrightarrow{HCA_\beta} = \left|\overrightarrow{U_2}, \overrightarrow{O_\beta} - \vec{O}\right| \tag{42}$$

$$\overrightarrow{HCA_\gamma} = \left|\overrightarrow{U_3}, \overrightarrow{O_\delta} - \vec{O}\right| \tag{43}$$

$\overrightarrow{O_\alpha}$ - Leading best search agent

$\overrightarrow{O_\beta}$ - Succeeding best search agent

$\overrightarrow{O_\delta}$ - Third search agent

$$\overrightarrow{O_1} = \overrightarrow{O_\alpha} - \overrightarrow{Q_1} . (\overrightarrow{HCA_\alpha}) \tag{44}$$

$$\overrightarrow{O_2} = \overrightarrow{O_\beta} - \overrightarrow{Q_2} . (\overrightarrow{HCA_\beta}) \tag{45}$$

$$\overrightarrow{O_3} = \overrightarrow{O_\delta} - \overrightarrow{Q_3} . (\overrightarrow{HCA_\delta}) \tag{46}$$

$$\overline{O}(t+1) = \frac{\overrightarrow{O_1} + \overrightarrow{O_2} + \overrightarrow{O_3}}{3} \tag{47}$$

$\overrightarrow{O_\alpha}$ - Leading best search agent

$\overrightarrow{O_\beta}$ - Succeeding best search agent

$\overrightarrow{O_\delta}$ - Third search agent

Penetrating and confronting of the victim is modeled scientifically by presumptuous " $\vec{e}$ " (arbitrary) in the fissure of [2e,-2e]; while the $\vec{e} <$

1 Canis lupus dingo are enforced to round the victim and while $\vec{e} > 1$ adherents of the Canis lupus dingo population has to diverge from the victim. In the procedure exploration is done through penetrating of the prey and exploitation is done through confronting the prey.

In Sine Cosine Algorithm (SCA) maiden arbitrary agent solutions will swipe externally or interior way on the way to the premium solution by means of numerical archetypal which grounded on sine and cosine functions.

$$\vec{Z}_i^{t+1} = \vec{Z}_i^t + R_1 \times \sin(R_2) \times \left|R_3 \times I_i^t - \vec{Z}_i^t\right| \quad (48)$$

$$\vec{Z}_i^{t+1} = \vec{Z}_i^t + R_1 \times \cos(R_2) \times \left|R_3 \times I_i^t - \vec{Z}_i^t\right| \quad (49)$$

$$\vec{Z}_i^{t+1} = \begin{cases} \vec{Z}_i^t + R_1 \times \sin(R_2) \times \left|R_3 \times I_i^t - \vec{Z}_i^t\right| & R_4 < 0.5 \\ \vec{Z}_i^t + R_1 \times \cos(R_2) \times \left|R_3 \times I_i^t - \vec{Z}_i^t\right| & R_4 \geq 0.5 \end{cases} \quad (50)$$

In order to evade to be stuck in local optima Canis lupus dingo algorithm mongrelized with sine cosine algorithm (HCSC) alpha representative of the Canis lupus dingo is boosted by sine cosine algorithm. Through this exploration and exploitation is poised and upgraded. Fig b shows Flow chart of Hybridized Canis lupus dingo algorithm with Sine Cosine Algorithm. Convergence precision is improved by smearing position streamline and to balance the exploration and the exploitation technique of the proposed algorithm. Over this the rationalized equation is described as follows,

$$\overrightarrow{HCA_\alpha} = \begin{cases} R\,() \times \sin(R()) \times \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right| R() < 0.5 \\ R() \times \cos(R()) \times \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right| R() \geq 0.5 \end{cases} \quad (51)$$

$$\overrightarrow{O_1} = \overrightarrow{O_\alpha} - \overrightarrow{Q_1}\ .\left(\overrightarrow{HCA_\alpha}\right) \quad (52)$$

a. Start
b. Initialization of population
c. Set the parameters
d. $\overrightarrow{O_\alpha}$ - Leading best search agent
e. $\overrightarrow{O_\beta}$ - Succeeding best search agent
f. $\overrightarrow{O_\delta}$ - Third search agent
g. While (t< max iter number)
h. Location of the contemporary search agent rationalized
i. $\bar{O}(t+1) = \frac{\overrightarrow{O_1}+\overrightarrow{O_2}+\overrightarrow{O_3}}{3}$
j. End for
k. Refurbishment of standards
l. $\vec{Q} = 2\vec{e}.r_1 - \vec{e}$
m. $\vec{U} = 2.r_2$
n. $\vec{e} = 2 - 2t/t_{max}$
o. Exploration agent's fitness rate is calculated
p. Modernize the values
q. $\overrightarrow{O_1} = \overrightarrow{O_\alpha} - \overrightarrow{Q_1}\ .\left(\overrightarrow{HCA_\alpha}\right)$
r. $\overrightarrow{O_2} = \overrightarrow{O_\beta} - \overrightarrow{Q_2}\ .\left(\overrightarrow{HCA_\beta}\right)$
s. $\overrightarrow{O_3} = \overrightarrow{O_\delta} - \overrightarrow{Q_3}\ .\left(\overrightarrow{HCA_\delta}\right)$
t. If $R() < 0.5$
u. $R\,() \times \sin(R()) \times \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right|$ $R() < 0.5$
v. Otherwise
w. $R() \times \cos(R()) \times \left|\overrightarrow{U_1}, \overrightarrow{O_\alpha} - \vec{O}\right|$ $R() \geq 0.5$
x. $\overrightarrow{O_1} = \overrightarrow{O_\alpha} - \overrightarrow{Q_1}\ .\left(\overrightarrow{HCA_\alpha}\right)$
y. End if
z. End else
aa. End while
bb. Return the $\overrightarrow{O_\alpha}$
cc. End

5. Simulation Results

Proposed HNLTL and HCSC are appraised substantiated in IEEE 30 bus system. 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. Predominantly voltage stability augmentation accomplished with minimized voltage deviation. In Table 1 show the loss assessment, Table 2 shows the voltage deviation evaluation and Table 3 gives the L-index review. Comparison done with BPSO-TS [10],TS[10],BPSO [10],ALO [11],QO-TLBO [12],TLBO [12],SGA [13],BPSO [13],HAS [13],S-FS [14],IS-FS [14] and SFS [16] algorithms. Figs 1 to 3 shows the comparison of parameters.

Table 1: Appraisal of power loss

Technique	**Power loss (MW)**
Regular PSO-TS [10]	4.5213
Customary TS [10]	4.6862

Basic PSO [10]	4.6862
Standard ALO [11]	4.5900
Basic QO-TLBO [12]	4.5594
Original TLBO [12]	4.5629
Standard GA [13]	4.9408
Basic PSO [13]	4.9239
Hybrid -AS [13]	4.9059
Regular FS [14]	4.5777
Hybrid -ISFS [14]	4.5142
Regular FS [16]	4.5275
HNLTL	4.4988
HCSC	4.4982

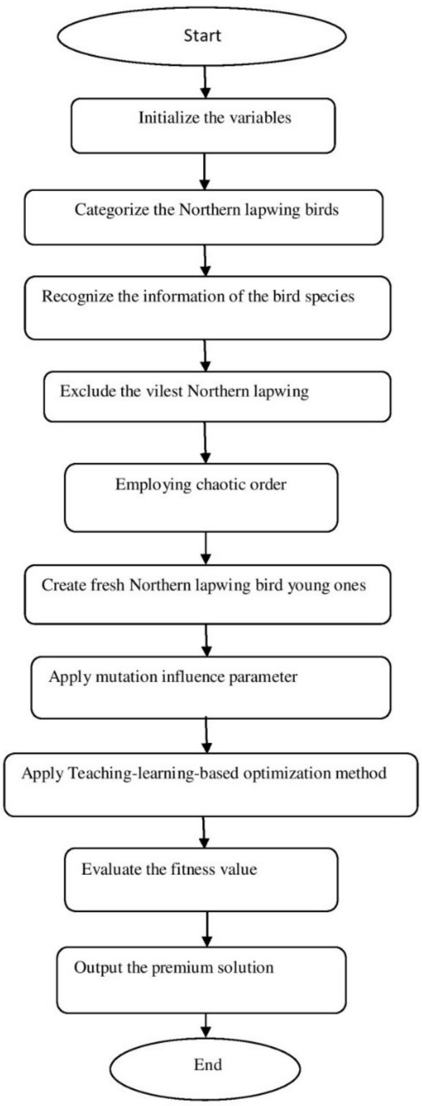

Fig. a: Flow chart of Hybridized Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL)

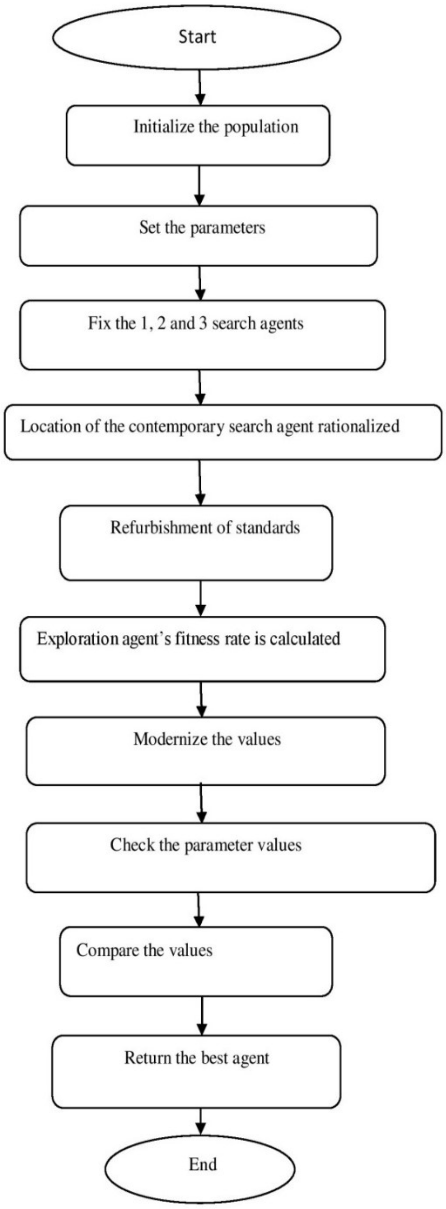

Fig. b: Flow chart of Hybridized Canis lupus dingo algorithm with Sine Cosine Algorithm

In the Fig. 1 comparison of real power loss done with other reported algorithms; Regular PSO-TS [10], Customary TS [10], Basic PSO [10], Standard ALO [11], Basic QO-TLBO [12], Original TLBO [12], Standard GA [13], Basic PSO [13], Hybrid -AS [13], Regular FS [14], Hybrid -ISFS [14] and Regular FS [16].

In Fig. 2 comparison of voltage deviation done with Standard PSO-TVIW [15], Basic PSO-TVAC [15], Hybrid -PSOTVAC [15], Regular PSO-CF [15], Hybrid -PGPSO [15], Basic SWT-PSO [15], Basic PGSWT-PSO [15], Hybrid-MPGPSO [15], Hybrid -QOTLBO [12], Original

TLBO [12], Regular FS [14], Enhanced SFS [14] and Customary FS [16].

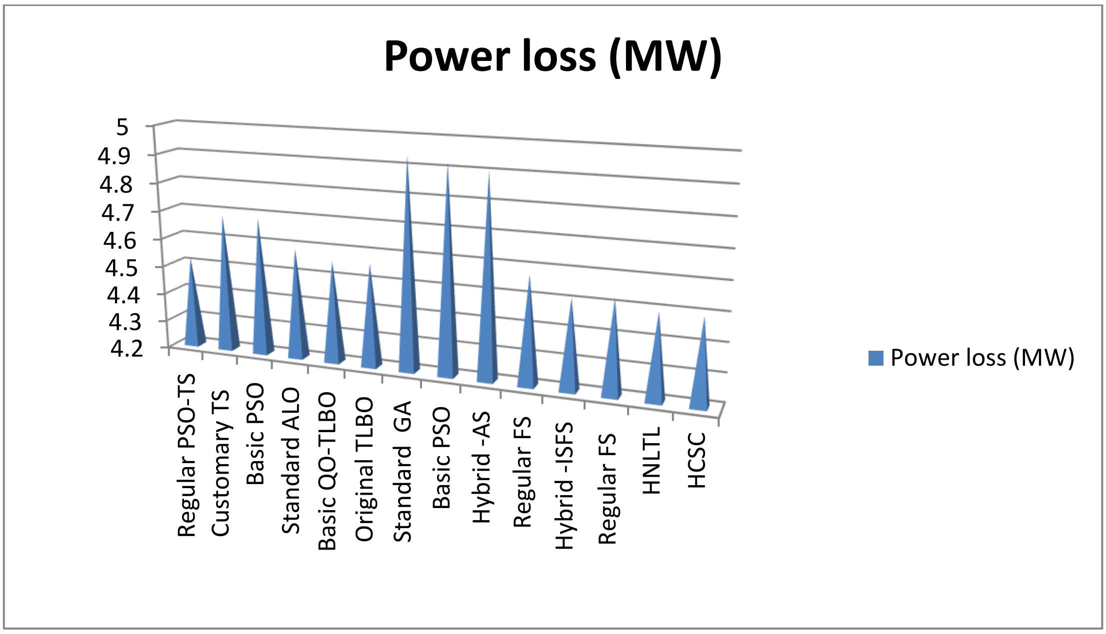

Fig. 1: Power loss comparison (X axis- Methods, Y-axis – Value of Power loss in MW)

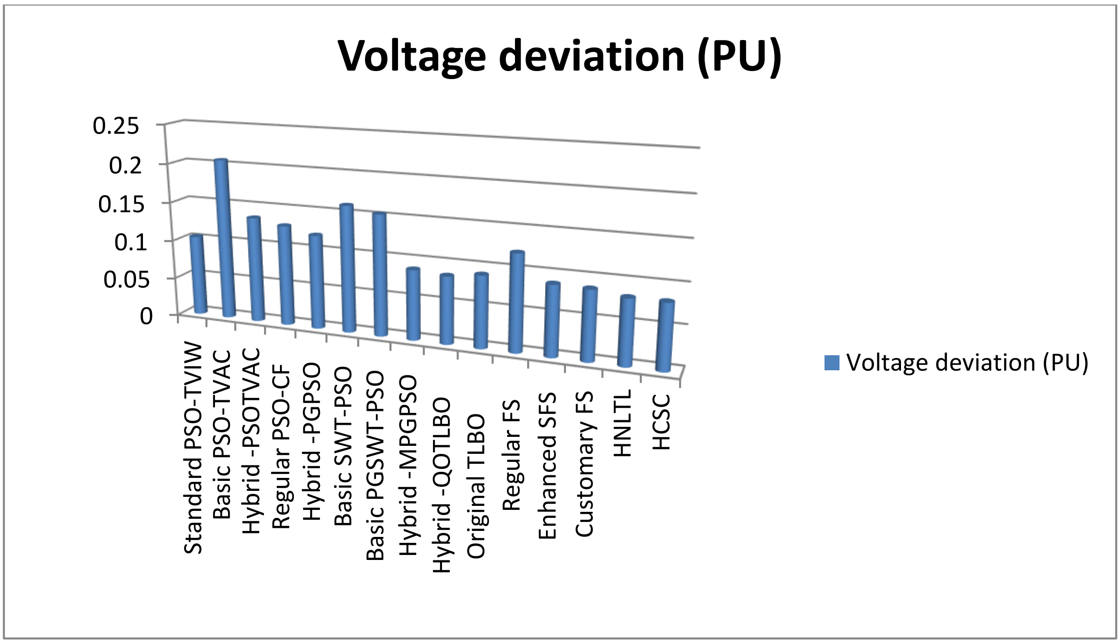

Fig. 2: Comparison of Voltage deviation (X axis- Methods, Y-axis –value of Voltage deviation in PU)

Table 2: Evaluation of voltage deviation

Technique	Voltage deviation (PU)
Standard PSO-TVIW [15]	0.1038
Basic PSO-TVAC [15]	0.2064
Hybrid -PSOTVAC [15]	0.1354
Regular PSO-CF [15]	0.1287
Hybrid -PGPSO [15]	0.1202
Basic SWT-PSO [15]	0.1614
Basic PGSWT-PSO [15]	0.1539
Hybrid -MPGPSO [15]	0.0892
Hybrid -QOTLBO [12]	0.0856
Original TLBO [12]	0.0913
Regular FS [14]	0.1220
Enhanced SFS [14]	0.0890
Customary FS [16]	0.0877
HNLTL	0.0821
HCSC	0.0819

Table 3: Appraisal of VSI for IEEE 30 bus system

Technique	L-index (PU)
Original PSO-TVIW [15]	0.1258
Hybrid -PSOTVAC [15]	0.1499
Basic PSO-TVAC [15]	0.1271
Hybrid -BPSOCF [15]	0.1261
Basic PG-PSO [15]	0.1264
Hybrid -SWTPSO [15]	0.1488
Basic PGSWT-PSO [15]	0.1394
Hybrid -MPGPSO [15]	0.1241
Basic QO-TLBO [12]	0.1191
Regular TLBO [12]	0.1180
ALO [11]	0.1161
Original ABC [11]	0.1161
Basic GWO [11]	0.1242
Standard BA [11]	0.1252
Regular FS [14]	0.1252
Enhanced SFS [14]	0.1245
Customary FS [16]	0.1007
HNLTL	0.1003
HCSC	0.1001

In Fig. 3 comparison of voltage stability done with Basic PG-PSO [15], Hybrid -SWTPSO [15], Basic PGSWT-PSO [15], Hybrid -MPGPSO [15], Basic QO-TLBO [12], Regular TLBO [12], ALO [11], Original ABC [11], Basic GWO [11], Standard BA [11], Regular FS [14], Enhanced SFS [14] and Customary FS [16].

At first in standard IEEE 14 bus system the validity of the Proposed HNLTL and HCSC has been tested, Table 4 shows comparison results. Figures 4 to 8 shows the comparison of power loss.

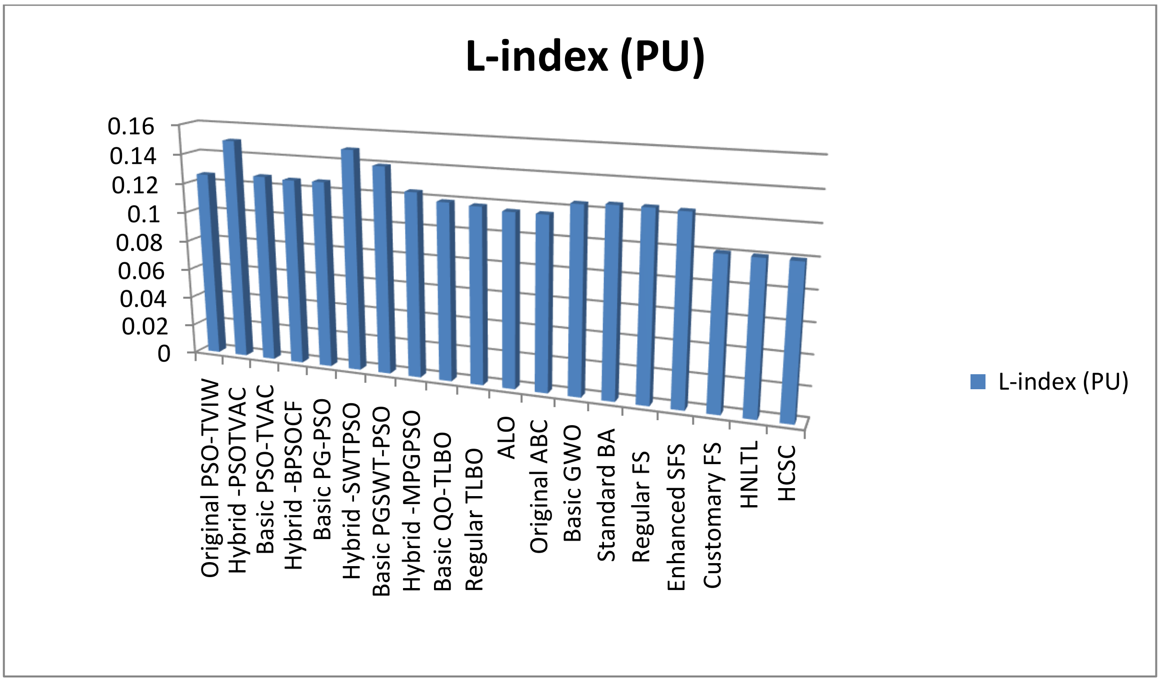

Fig. 3: Comparison of voltage stability (L-index) (X axis- Methods, Y-axis –value of L index in PU)

Table 4: Comparison of loss (IEEE −14 system)

Parameters	Base case [19]	MPSO [19]	PSO [24]	EP [22]	SARGA [23]	HNLTL	HCSC
Percentage of Reduction in Power Loss	0	9.2	9.1	1.5	2.5	17.73	25.40
Power loss in MW	13.550	12.293	12.315	13.346	13.216	11.147	10.108

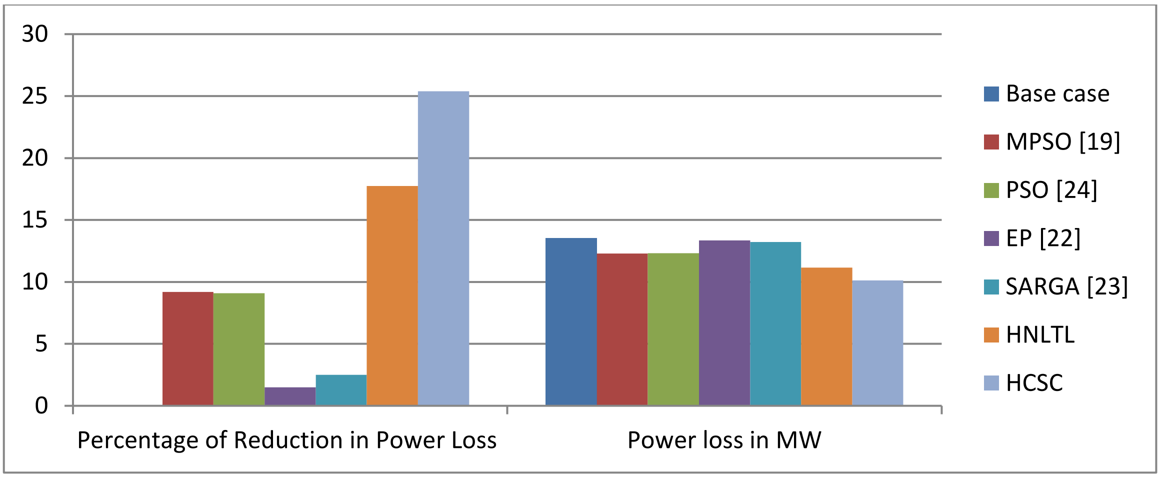

Fig. 4: Comparison of Power Loss (X axis- Methods, Y-axis – Value and percentage of reduction of Power loss (MW))

In Fig. 4 comparison of real power loss (IEEE 14 bus system) has been done with MPSO [19], PSO [24], EP [22] and SARGA [23]. Proposed HNLTL and HCSC reduced the power loss efficiently.

Then the Proposed HNLTL and HCSC have been tested, in IEEE 30 Bus system. Comparison results are presented in Table 5.

In Fig. 5 comparison of real power loss (IEEE 30 bus system) has been done with MPSO [19], PSO [24], EP [22] and SARGA [23]. Proposed HNLTL and HCSC reduced the power loss efficiently.

Then the Proposed HNLTL and HCSC have been tested, in IEEE 57 Bus system [18]. Table 6 shows the comparison results.

Table 5: Comparison of results (IEEE −30 system)

Parameters	Base case [19]	MPSO [19]	PSO [24]	EP [22]	SARGA [23]	HNLTL	HCSC
Percentage of Reduction in Power Loss	0	8.4	7.4	6.6	8.3	13.95	17.97
Power loss in MW	17.55	16.07	16.25	16.38	16.09	15.101	14.396

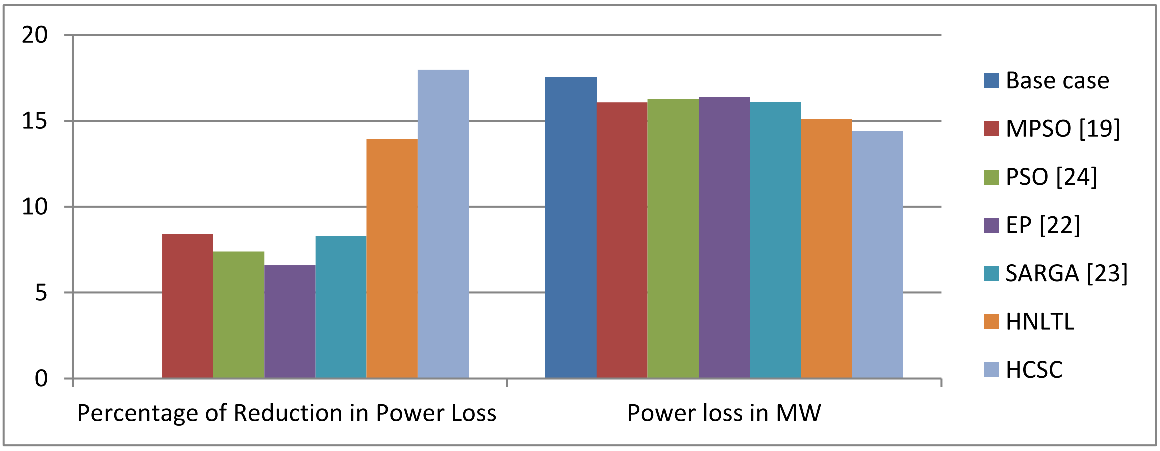

Fig. 5: Real power loss comparison (X axis- Methods, Y-axis – Value and percentage of reduction of Power loss (MW))

Table 6: Active power loss comparison (IEEE −57 system)

Parameters	Base case [19]	MPSO [19]	PSO [24]	CGA [23]	AGA [23]	HNLTL	HCSC
Percentage of Reduction in Power Loss	0	15.4	14.1	9.2	11.6	22.92	24.38
Power loss in MW	27.8	23.51	23.86	25.24	24.56	21.428	21.020

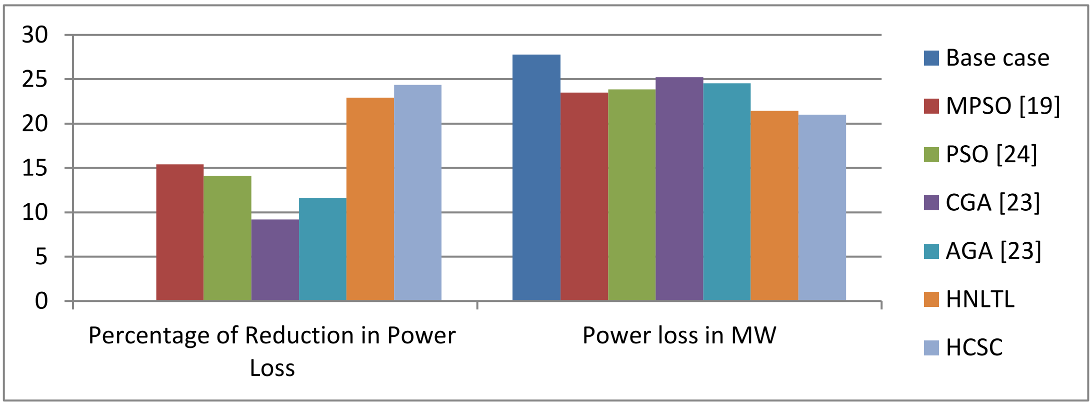

Fig. 6: Active power loss comparison (X axis- Methods, Y-axis – Value and percentage of reduction of Power loss (MW))

In Fig. 6 comparison of real power loss (IEEE 57 bus system) has been done with MPSO [19], PSO [24], CGA [23] and AGA [23]. Proposed HNLTL and HCSC reduced the power loss efficiently.

Then the Proposed HNLTL and HCSC have been tested, in IEEE 118 Bus system. Comparison results are presented in Table 7.

Table 7: Comparison of results (IEEE −118 system)

Parameter	Base case [19]	MPSO [19]	PSO [24]	IPSO [22]	CLPSO [22]	HNLTL	HCSC
Percentage of Reduction in Power Loss	0	11.7	10.1	0.6	1.3	13.29	13.95
Power loss in MW	132.8	117.19	119.34	131.99	130.96	115.139	114.269

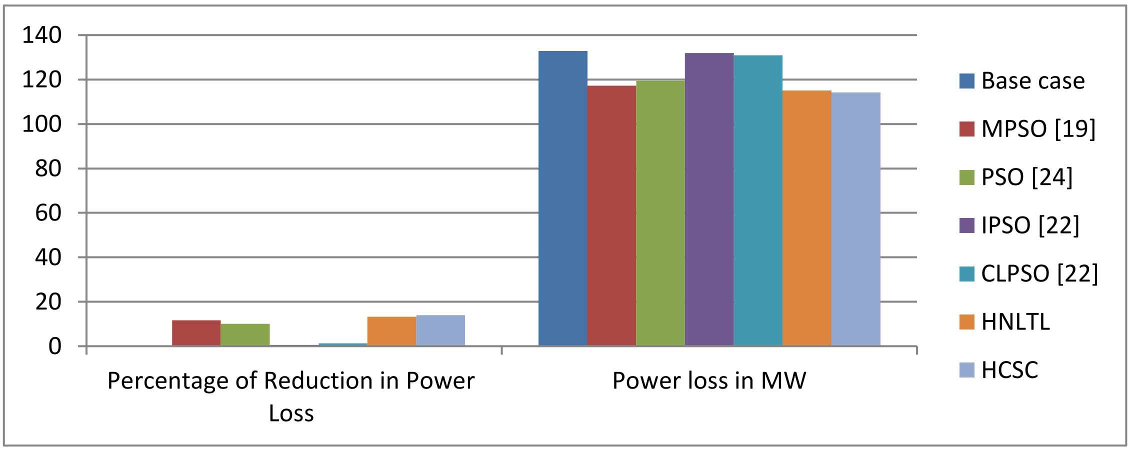

Fig. 7: Comparison of real power loss (X axis- Methods, Y-axis – Value and Percentage of reduction of Power loss (MW))

Table 8: Comparison of Real Power Loss

Parameter	EGA [21]	EEA [21]	CSA [20]	HNLTL	HCSC
Power loss (MW)	646.2998	650.6027	635.8942	613.4199	612.0100

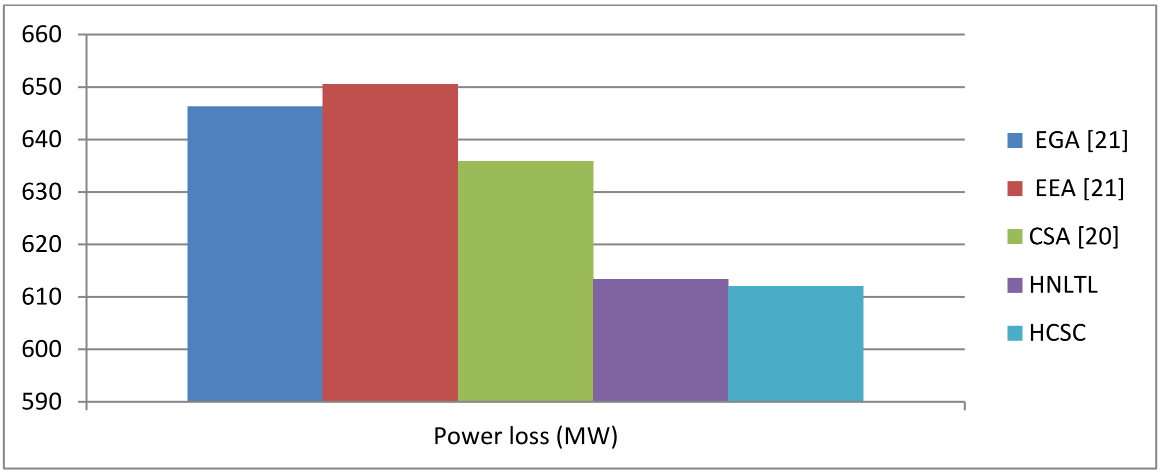

Fig. 8: Comparison of Active power loss (X axis- Methods, Y-axis – Value of Power loss in MW)

In Fig. 7 comparison of real power loss (IEEE 118 bus system) has been done with MPSO [19], PSO [24], IPSO [22] and CLPSO [22]. Proposed HNLTL and HCSC reduced the power loss efficiently.

Then IEEE 300 bus system is used as test system to validate the performance of the Proposed HNLTL and HCSC. Table 8 shows the comparison of real power loss obtained after optimization.

In Fig. 8 comparison of real power loss (IEEE 300 bus system) has been done with EGA [21], EEA [21] and CSA [20]. Proposed HNLTL and HCSC reduced the power loss efficiently.

6. Conclusion

In this work Hybridization of Northern lapwing mating optimizer algorithm with Teaching-learning-based optimization algorithm (HNLTL) successfully solved the optimal reactive power problem. In the commencement of the projected hybridized algorithm, TLBO operator with commanding exploration capability with large P_c value enlarged the solution space. Then to get the most excellent solution NLM operator will search with small P_c value in local mode. Both exploration and exploitation has been improved. In this work hybridization of Canis lupus dingo algorithm with Sine Cosine Algorithm (HCSC) successfully solved the optimal reactive power problem. Through the hybridization progress of alpha representative of the Canis lupus dingo has been enhanced based on sine cosine algorithm. Both exploration and exploitation has been maintained in balanced mode in the projected algorithm. Proposed HNLTL and HCSC are appraised in IEEE 30 bus system with power constancy. Proposed HNLTL and HCSC has been tested in standard IEEE 14, 30, 57,118 and 300 bus test systems deprived of power constancy. Simulation results show the planned HNLTL and HCSC algorithms are abridged the power loss competently.

After hybridization the obtained real power loss (IEEE 30 Bus system) as follows

1. With considering voltage stability (multi objective); HNLTL- 4.4988 (MW) and HCSC-4.4982 (MW)
2. Without considering voltage stability (single objective) ; HNTL- 15.101(MW) and HCSC -14.396 (MW)

The work has been enhanced and real power loss reduction has been attained. Comparison has been done with other standard reported algorithms

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