EXTREME LEARNING MACHINE AND CHAOTIC BASED SPHYRAENA CHRYSOTAENIA OPTIMIZATION ALGORITHMS FOR LOSS LESSENING AND POWER STABILITY MAGNIFICATION

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Abstract

In this paper Extreme Learning Machine and Chaotic based Sphyraena Chrysotaenia Optimization Algorithms are applied for solving the Real Power loss lessening problem. Key objective of this work are Real power loss decreasing, power divergence restraining, and power constancy amplification. Extreme Learning machine and chaotic are integrated in the algorithm to obtain the better solutions. Candidate solutions in the projected Sphyraena Chrysotaenia optimization are Sphyraena Chrysotaenia and population in the inspection region is quixotically enthused. Spasmodically impressive solutions can be erroneous while restructuring the position of inspection agents and renewed positions may be inadequate one than the previous positions so magnificent selection is engaged. Domination comprises recurrence the self-effacing fitting solution to ensuing generation. In Extreme Learning Machine based Sphyraena Chrysotaenia Optimization Algorithm (ELMSC) initial phases of iteration, the Sphyraena Chrysotaenia Optimization Algorithm contestants are diversified in position and exponential standby generates unrestricted impulsive calculations which endow the rudiments to accommodate the entire revelation area. Compatibly, all over end stage of iterations, fundamentals are enclosed by Sphyraena Chrysotaenia Optimization Algorithm contestants and all an optimal condition with equivalent scheme. Chaotic sequences are combined into the Sphyraena Chrysotaenia Optimization Algorithm (CSCO). This amalgamation will augment the Exploration and Exploitation. Tinkerbell chaotic map fabricating tenets are employed. Proposed ELMSC and CSCO are corroborated in IEEE 30, 57, 118, 300, and 354 bus test systems. True power loss lessening, power divergence curtailing, and power constancy augmentation has been achieved. In future proposed ELMSC and CSCO can be applied to solve the others problems in Electrical engineering and also can be applied to resolve the problems in other engineering domains.

Keywords: **Chaotic, optimal, reactive, sphyraena chrysotaenia extreme learning, machine, transmission loss**

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Introduction

Real power Loss lessening problem in system is planned as one of the farfetched atmospheres for safe and budgetary operation.

The problem solved by modified interior point method (Zhu and Xiong, 2003), successive quadratic programming (Quintana and Santos-Nieto, 1989), Newton-Raphson (Jan and Chen, 1995), Security-constrained mode (Terra and Short, 1991), successive quadratic programming (Grudinin, 1998), Marine Predators Algorithm (Ebeed *et al*., 2020), Hybrid Algorithm (Sahli *et al*., 2018), semidefinite method (Davoodi *et al*., 2019), Tight-and-cheap conic relaxation (Bingane *et al*., 2019), Hybridized PSO-Tabu (Sahli *et al*., 2014), Ant lion algorithm (Mouassa and Bouktir, 2019), quasi-oppositional (Mandal, and Roy, 2013), Harmony search procedure (Khazali and Kalantar, 2011).

Then Fractal search (Tran *et al*., 2019), pseudo-gradient method (Polprasert *et al*., 2016), Operative Metaheuristic Procedure (Duong *et al*., 2020), Bagging based ELM (Raghuwanshi and Shukla, 2019), Dual-Weighted Kernel ELM (Yu *et al*., 2021), kernel ELM (Lv and Han, 2019), Seeker optimization (Dai *et al*., 2009), self-adaptive real coded Genetic procedure (Subbaraj and Rajnarayanan, 2009), Particle swarm optimization (Pandya and Roy, 2015), Amended Particle Swarm Optimization (Hussain *et al*., 2018), Enhanced Particle Swarm Optimization (Vishnu and Sunil Kumar, 2020), Design Algorithm for the Logistics (Omelchenko *et al*., 2020a), organization of logistic systems of scientific productions (Omelchenko *et al*., 2020b), the Problems and organizational and technical solutions (Omelchenko *et al*., 2020c) are applied.

Then Slime Mould Algorithm (Khunkitti *et al*., 2021), Optimization Techniques (Diab *et al*., 2021), faster and cuckoo search algorithms (Reddy *et al*., 2014; Salkuti, 2017), ALO method (Sridhar and Kowsalya, 2021), moth flame optimization procedure (Suja, 2021), grasshopper optimization algorithm (Falehi, 2020), hybrid ABC-PSO (Sharma and Ghosh, 2020), dragonfly algorithm (Saravanan and Anbalagan, 2021), Improved moth-swarm algorithm (Bentouati *et al*., 2021), OS-DPLL (Menon *et al*., 2021), STATCOM (Saxena, *et al*., 2021), Loop Configuration (Kazmi, *et al*., 2017) EDN (Sambaiah and Jayabarathi, 2020), in var comp.optimal Location (Zaidan and Toos, 2021), GWO-BSA (Priya and Christa, 2021), ESR (Ahmadnia *et al*., 2019), Thyristor-controlled Phase Shifting (Ashpazi *et al*., 2015), Fuzzy-Controlled Differential Evolution (Juneja, 2020), Discrete Values of Capacitors and Tap Changers (Kien *et al*., 2021), Multi-objective ant lion optimization (Mouassa *et al*., 2019), Improved Salp Swarm Algorithm (Tudose *et al*., 2021), Levy Interior Search Algorithm (Nagarajan *et al*., 2020), moth-flame optimization technique (Mei *et al*., 2017), grey wolf optimizer (Nuaekaew *et al*., 2017), Multi-objective enhanced PSO algorithm (Chen *et al*., 2016) are applied.

Masood *et al.* (2022) worked in PV applications. Musarat *et al.* (2021) worked in ARIMA forecasting. Wang *et al*. (2022) worked in ELM. Nafees *et al.* (2021) worked in beam column.

In this paper Extreme Learning Machine and Chaotic based Sphyraena Chrysotaenia Optimization Algorithms are applied for solving the Power loss lessening problem. Sphyraena Chrysotaenia is avaricious and decadent magnificent fish in the nautical which attack the Herring for sustenance. Passage of Sphyraena Chrysotaenia is in rise mode, it attack the Herring vigorously and it incompetent to gush from the attack done by Sphyraena Chrysotaenia.

The systematic activities of Sphyraena Chrysotaenia are imitated to design the Sphyraena Chrysotaenia optimization algorithm to solve loss lessening problem. Candidate solutions in the projected Sphyraena Chrysotaenia optimization are Sphyraena Chrysotaenia and population in the inspection region is quixotically enthused. Spasmodically impressive solutions can be erroneous while restructuring the position of inspection agents and renewed positions may be inadequate one than the previous positions so magnificent selection is engaged. Domination comprises recurrence the self-effacing fitting solution to ensuing generation.

- Candidate solutions in the projected Sphyraena Chrysotaenia optimization are Sphyraena Chrysotaenia and population in the inspection region is quixotically enthused.
- Spasmodically impressive solutions can be erroneous while restructuring the position of inspection agents and renewed positions may be inadequate one than the previous positions so magnificent selection is engaged. Domination comprises recurrence the self-effacing fitting solution to ensuing generation.

Power loss minimization is defined by

$$Min\ \tilde{F}(\bar{d}, \bar{e}) \tag{1}$$

where min is minimization of power loss

Subject to the constraints

$$A(\bar{d},\bar{e}) = 0 \quad (2)$$

$$B(\bar{d},\bar{e}) = 0 \quad (3)$$

where d, e are control and dependent variables.

$$d = [VLG_1, .., VLG_{Ng}; QC_1, .., QC_{Nc}; T_1, .., T_{N_T}] \quad (4)$$

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

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,

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

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

$$F_3 = Minimize\ L_{MaxImum} \quad (8)$$

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

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

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

Parity constraints

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

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

Disparity constraints

$$P_{gslack}^{minimum} \le P_{gslack} \le P_{gslack}^{maximum} \quad (14)$$

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

$$VL_i^{minimum} \le VL_i \le VL_i^{maximum}, i \in NL \quad (16)$$

$$T_i^{minimum} \le T_i \le T_i^{maximum}, i \in N_T \quad (17)$$

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

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

$$VG_i^{minimum} \le VG_i \le VG_i^{maximum}, i \in N_g \quad (20)$$

$$Multi\ objective\ fitness\ (MOF) = F_1 + r_i F_2 + u F_3 = F_1 + \left[\sum_{i=1}^{NL} x_v [VL_i - VL_i^{min}]^2 + \sum_{i=1}^{NG} r_g [QG_i - QG_i^{min}]^2\right] + r_f F_3 \quad (21)$$

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

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

Methods: Extreme Learning Machine and Chaotic based Sphyraena Chrysotaenia Optimization Algorithm

Sphyraena Chrysotaenia is avaricious and decadent magnificent fish in the nautical which attack the Herring for sustenance. Passage of Sphyraena Chrysotaenia is in rise mode, it attack the Herring vigorously and it incompetent to gush from the attack done by Sphyraena Chrysotaenia. The systematic activities of Sphyraena Chrysotaenia are imitated to design the Sphyraena Chrysotaenia optimization algorithm to solve loss lessening problem. Candidate solutions in the projected Sphyraena Chrysotaenia optimization are Sphyraena Chrysotaenia and population in the inspection region is quixotically enthused. In the piercing region of current position of the ith aficionado is demarcated as,

$$W_{i,k} \in \mathcal{B}(i = 1,2, .., n) \quad (24)$$

Impulsive position in the technique is demarcated as,

$$W_P = \begin{bmatrix} W_{1,1} & W_{1,2} \cdots W_{1,d} \\ W_{2,1} & W_{2,2} \cdots W_{2,d} \\ \vdots & \vdots \cdots \vdots \\ W_{n,1} & W_{n,2} \cdots W_{n,d} \end{bmatrix} \quad (25)$$

where W_P indicate the position of Sphyraena Chrysotaenia.

Fitness degree is calculated as,

$$W_P = \begin{bmatrix} f(W_{1,1} & W_{1,2} \cdots W_{1,d}) \\ f(W_{2,1} & W_{2,2} \cdots W_{2,d}) \\ \vdots & \vdots \cdots \vdots \\ f(W_{n,1} & W_{n,2} \cdots W_{n,d}) \end{bmatrix} = \begin{bmatrix} F_{W1} \\ F_{W2} \\ \vdots \\ F_{Wn} \end{bmatrix} \quad (26)$$

Herring group is united in Sphyraena Chrysotaenia method and in the inspection zone it's twirling. At that period the Herring position and fitness are is calculated as,

$$H_P = \begin{bmatrix} H_{1,1} & H_{1,2} \cdots H_{1,d} \\ H_{2,1} & H_{2,2} \cdots H_{2,d} \\ \vdots & \vdots \cdots \vdots \\ H_{n,1} & H_{n,2} \cdots H_{n,d} \end{bmatrix} \quad (27)$$

where H_P indicate the position of Herring.

$$H_P = \begin{bmatrix} f(H_{1,1} & H_{1,2} \cdots H_{1,d}) \\ f(H_{2,1} & H_{2,2} \cdots H_{2,d}) \\ \vdots & \vdots \cdots \vdots \\ f(H_{n,1} & H_{n,2} \cdots H_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{H1} \\ F_{H2} \\ \vdots \\ F_{Hn} \end{bmatrix} \quad (28)$$

Spasmodically impressive solutions can be erroneous while restructuring the position of inspection agents and renewed positions may be inadequate one than the previous positions so magnificent selection is engaged. Domination comprises recurrence the self-effacing fitting solution to ensuing generation. The position of the magnificent Sphyraena Chrysotaenia and the assaulted Herring which possess the excellent fitness degree is designated as,

$$O^i_{M\_W}; O^i_{A\_H} \quad (29)$$

where $O^i_{M_W}$ indicate magnificent Sphyraena Chrysotaenia

$O^i_{A\_H}$ Specify the assaulted Herring

In the proposed Sphyraena Chrysotaenia method the renewed position of Sphyraena Chrysotaenia labeled as,

$$O^i_{new_W} = O^i_{M\_W} - \delta_i \times \left(R * \left(\frac{O^i_{M\_W} + O^i_{A\_H}}{2}\right) - O^i_{GW}\right) \quad (30)$$

$$\sigma_i = 2.0 * R * L - L \quad (31)$$

$$R \in [0,1]$$
$$H = 1 - \left(\frac{\text{no. of Sphyraena Chrysotaenia}}{\text{no. of Sphyraena Chrysotaenia } + \text{no. of Herring}}\right) \quad (32)$$

All over the persecution the renewed position of the Herring is quantified as,

$$O^i_{new\_H} = R \times \left(O^i_{M\_W} - O^i_{GW} + AK\_W\right) \quad (33)$$

where AK_W indicate the attack of Sphyraena Chrysotaenia

O^i_{GW} specify previous Sphyraena Chrysotaenia

$$AK = U \times (2 * \text{iteration} * \varphi) \quad (34)$$

By Attack control capacity, Herring will rationalize the location

$$\gamma = Sum_H \times AT \quad (35)$$

$$\delta = V \times AT \quad (36)$$

where γ, δ specify the position and parameter

Sum_H is the quantity of Herring

Possibilities of Sphyraena Chrysotaenia to shoot fresh Herring is demarcated as,

$$O^i_W = O^i_Y, \text{if } f(H_i) < f(W_i) \quad (37)$$

a. Start
b. Fix the parameters
c. Produce the Sphyraena Chrysotaenia population
d. Randomly Generate Herring population
e. Calculate the fitness degree of Sphyraena Chrysotaenia
f. Estimate the fitness value of Herring
g. Fix magnificent Sphyraena Chrysotaenia
h. Set assaulted Herring
i. While end condition is not attained
j. For each Sphyraena Chrysotaeniacalculate the value of σ_i
k. $\sigma_i = 2.0 * R * L - L$
l. Restructure the Sphyraena Chrysotaenia position
m. $O^i_{new_W} = O^i_{M\_W} - \delta_i \times \left(R * \left(\frac{O^i_{M\_W} + O^i_{A\_H}}{2}\right) - O^i_{GW}\right)$
n. End for
o. Compute the attack control of Sphyraena Chrysotaenia
p. $AK = U \times (2 * \text{iteration} * \varphi)$
q. If $AK < 0.5$, then
r. Calculate γ, δ
s. $\gamma = Sum_H \times AT$
t. $\delta = V \times AT$

u. Based on γ , δ choose the set of Herring
v. Streamline the position of Herring
w. $O^{i}_{new\_H} = R \times \left(O^{i}_{M\_W} - O^{i}_{GW} + AK\_W\right)$
x. End if
y. Compute fitness degree of all Herring
z. If enhanced Herring identified then interchange with assaulted Herring
aa. $O^{i}_{W} = O^{i}_{Y}$, if $f(H_i) < f(W_i)$
bb. Eliminate the hunted Herring
cc. Streamline the finest Sphyraena Chrysotaenia
dd. Modernize the supreme Herring
ee. End if
ff. End while
gg. Return preeminent Sphyraena Chrysotaenia
hh. End

Extreme learning machine (ELM) is applied and Linking neurons weight matrix of input to hidden layer is defined as,

$$Weight = \begin{bmatrix} weight_1^T \\ weight_2^t \\ ; \\ weight_l^T \end{bmatrix} = \begin{bmatrix} weight_{11} & \cdots & weight_{1n} \\ \vdots & \ddots & \vdots \\ weight_{L1} & \cdots & weight_{Ln} \end{bmatrix} \tag{38}$$

$$(nw.\beta) = \begin{bmatrix} nw.\beta_1^T \\ nw.\beta_2^t \\ ; \\ nw.\beta_l^T \end{bmatrix} = \begin{bmatrix} nw.\beta_{11} & \cdots & nw.\beta_{1n} \\ \vdots & \ddots & \vdots \\ weight_{L1} & \cdots & nw.\beta_{Ln} \end{bmatrix} \tag{39}$$

$$\text{Neurons hidden layer bias vector (bv)} = \begin{bmatrix} bv_1 \\ bv_2 \\ : \\ bv_L \end{bmatrix}_{L\times 1} \tag{40}$$

$$(z_i, G_i)\ ;\ z_i = [z_{i1}, z_{i2}, .., z_{idn}]^E \in SU^{dn}, G_i = [G_{i1}, G_{i2}, .., G_{idn}]^E \in SU^{dn},$$

$$(G) = \begin{bmatrix} G_1^T \\ G_2^t \\ ; \\ G_l^T \end{bmatrix} = \begin{bmatrix} G_{11} & \cdots & G_{1n} \\ \vdots & \ddots & \vdots \\ G_{L1} & \cdots & G_{Ln} \end{bmatrix} \tag{41}$$

$$\sum_{i=1}^{N} nw.\beta_i \cdot kn\left(\omega_i z_j + a_i\right) = G_j \tag{42}$$

$$(Q) \cdot (nw.\beta) = G \tag{43}$$

$$Q(z_1, .. z_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} kn(\omega_1 z_1 + a_1) & \cdots & kn(\omega_L z_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 z_N + a_1) & \cdots & kn(\omega_L z_N + a_L) \end{bmatrix} \tag{44}$$

$$nw.\beta = Q^{-1} \cdot g \tag{45}$$

a. Start
b. Data input
c. Begin the data Test and Training set
d. Rendering to the training set - regulate Q
e. $(z_1, .. z_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} kn(\omega_1 z_1 + a_1) & \cdots & kn(\omega_L z_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 z_N + a_1) & \cdots & kn(\omega_L z_N + a_L) \end{bmatrix}$
f. Control the output rate of weight
g. $nw.\beta = Q^{-1} \cdot g$
h. Rendering to the test set - evaluate S
i. $Q(z_1, .. z_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} kn(\omega_1 z_1 + a_1) & \cdots & kn(\omega_L z_1 + a_L) \\ \vdots & \ddots & \vdots \\ kn(\omega_1 z_N + a_1) & \cdots & kn(\omega_L z_N + a_L) \end{bmatrix}$
j. Calculate the actual rate through $nw.\beta$ and S
k. Computation of error grade
l. Valuation of actual value with credible rate

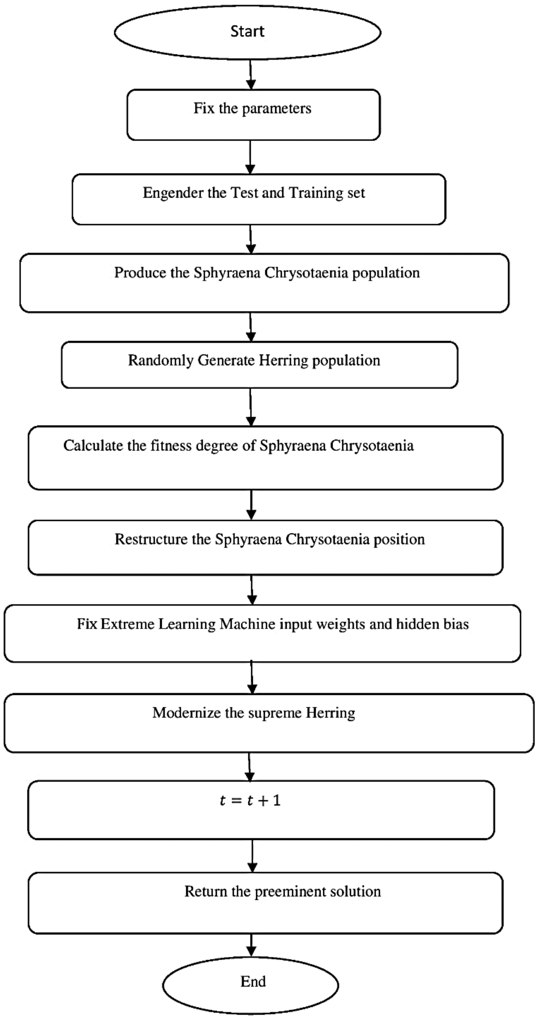

Figure 1. Flowchart of projected ELMSC

m. Return the error rate
n. End

In Extreme Learning Machine based Sphyraena Chrysotaenia Optimization Algorithm (ELMSC) predominantly all apparatuses don't own any info about the revelation zone. Figure 1 shows the Flowchart of ELMSC.

a. Start
b. Fix the parameters
c. Input the data
d. Engender the Test and Training set
e. Produce the Sphyraena Chrysotaenia population
f. Randomly Generate Herring population
g. Calculate the fitness degree of Sphyraena Chrysotaenia
h. Estimate the fitness value of Herring
i. Fix magnificent Sphyraena Chrysotaenia
j. Set assaulted Herring
k. While end condition is not attained
l. For each Sphyraena Chrysotaeniacalculate the value of σ_i
m. $\sigma_i = 2.0 * R * L - L$
n. Restructure the Sphyraena Chrysotaenia position
o. $O^i_{new_W} = O^i_{M\_W} - \delta_i \times \left(R * \left(\frac{O^i_{M\_W} + O^i_{A\_H}}{2}\right) - O^i_{GW}\right)$
p. End for
q. Compute the attack control of Sphyraena Chrysotaenia
r. $AK = U \times (2 * iteration * \varphi)$
s. If $AK < 0.5$, then
t. Calculate γ, δ
u. $\gamma = Sum_H \times AT$
v. $\delta = V \times AT$
w. Based on γ, δ choose the set of Herring
x. Streamline the position of Herring
y. $O^i_{new\_H} = R \times \left(O^i_{M\_W} - O^i_{GW} + AK\_W\right)$
z. End if
aa. Compute fitness degree of all Herring
bb. If enhanced Herring identified then interchange with assaulted Herring
cc. $O^i_W = O^i_Y$, if $f(H_i) < f(W_i)$
dd. Eliminate the hunted Herring
ee. Fix Extreme Learning Machine input weights and hidden bias
ff. Streamline the finest Sphyraena Chrysotaenia
gg. Modernize the supreme Herring
hh. End if
ii. End while
jj. Return preeminent Sphyraena Chrysotaenia
kk. End

Chaotic sequences (Inoue *et al.*, 2000) are integrated into the Sphyraena Chrysotaenia Optimization Algorithm (CSCO). Tinkerbell chaotic map producing canons are applied. Figure 2 shows the schematic diagram of CSCO

$$l_{t+1} = l_t^2 - m_t^2 + a \cdot l_t + b \cdot m_t \tag{46}$$

$$m_{t+1} = 2 l_t m_t + c \cdot l_t + d \cdot m_t \tag{47}$$

where a, b, c and d are non-zero parameters

Functional rate by direct ascending in Tinkerbell chaotic map (Zou *et al.*, 2018) is delineated as,

$$l^*_{t+1} = l_{t+1} - min(l)/max(l) - min(l) \tag{48}$$

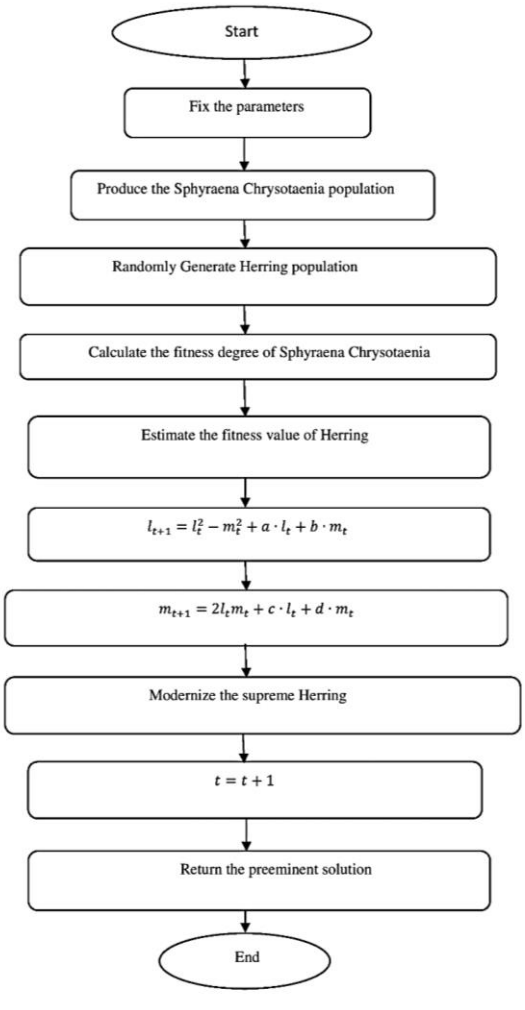

Figure 2. Schematic diagram of CSCO

a. Start
b. Fix the parameters
c. Produce the Sphyraena Chrysotaenia population
d. Randomly Generate Herring population
e. Calculate the fitness degree of Sphyraena Chrysotaenia
f. Estimate the fitness value of Herring
g. Fix magnificent Sphyraena Chrysotaenia
h. Set assaulted Herring
i. While end condition is not attained
j. For each Sphyraena Chrysotaeniacalculate the value of σ_i
k. $\sigma_i = 2.0 * R * L - L$
l. Restructure the Sphyraena Chrysotaenia position
m. $O^i_{new_W} = O^i_{M\_W} - \delta_i \times \left(R * \left(\frac{O^i_{M\_W} + O^i_{A\_H}}{2}\right) - O^i_{GW}\right)$
n. End for
o. Compute the attack control of Sphyraena Chrysotaenia
p. $AK = U \times (2 * \text{iteration} * \varphi)$
q. If $AK < 0.5$, then
r. Calculate γ, δ
s. $\gamma = Sum_H \times AT$
t. $\delta = V \times AT$
u. Based on γ, δ choose the set of Herring
v. Streamline the position of Herring
w. $O^i_{new\_H} = R \times (O^i_{M\_W} - O^i_{GW} + AK\_W)$
x. End if
y. Compute fitness degree of all Herring
z. If enhanced Herring identified then interchange with assaulted Herring
aa. $O^i_W = O^i_Y$, if $f(H_i) < f(W_i)$
bb. Eliminate the hunted Herring
cc. $l_{t+1} = l_t^2 - m_t^2 + a \cdot l_t + b \cdot m_t$
dd. $m_{t+1} = 2l_t m_t + c \cdot l_t + d \cdot m_t$
ee. $l^*_{t+1} = l_{t+1} - min(l)/max(l) - min(l)$
ff. Streamline the finest Sphyraena Chrysotaenia
gg. Modernize the supreme Herring
hh. End if
ii. End while
jj. Return preeminent Sphyraena Chrysotaenia
kk. End

Table 1. Assessment of tangible power loss

Method	Power loss (MW)
PSOTS (Sahli *et al.*, 2014)	4.5213
TS (Sahli *et al.*, 2014)	4.6862
PSO (Sahli *et al.*, 2014)	4.6862
A LOA (Mouassa *et al.*, 2017)	4.5900
QOTLBO (Mandal and Roy, 2013)	4.5594
TLBO (Mandal and Roy, 2013)	4.5629
GA (Khazali and Kalantar, 2011)	4.9408
SPSO (Khazali and Kalantar, 2011)	4.9239
HAS (Khazali and Kalantar, 2011)	4.9059
FS (Tran *et al.*, 2019)	4.5777
HIFS (Tran *et al.*, 2019)	4.5142
FS (Duong *et al.*, 2020)	4.5275
LISAI (Nagarajan *et al.*, 2020)	4.8193
LISAII (Nagarajan *et al.*, 2020)	4.8547
SSA (Tudose *et al.*, 2021)	4.5317
ISSA (Tudose *et al.*, 2021)	4.5269
ELMSC	4.3278
CSCO	4.3295

Results nd Discussion

Projected ELMSC and CSCO are corroborated in IEEE 30 bus system (Illinois Center for a Smarter Electric Grid, 2020). In Table 1 shows the loss assessment, Table 2 shows the power eccentricity evaluation and Table 3 gives the Power steadiness valuation. Figures 3 to 5 gives the graphical valuation.

Table 1 and Figure 3 shows the differnet values of loss obtained through various standard procedures and comparision done with the projected ELMSC and CSCO.

Table 2 and Figure 4 shows the power eccentricity evaluation and projected ELMSC,

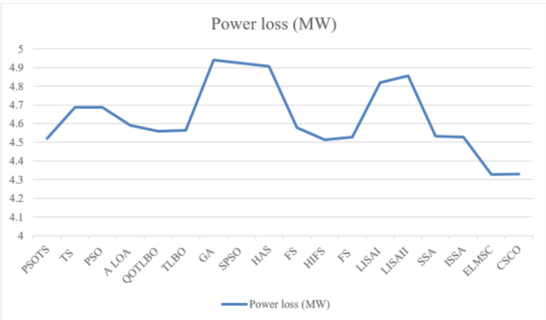

Figure 3. Assessment of tangible power loss (X-axis; Methods, Y-axis: value of loss in MW)

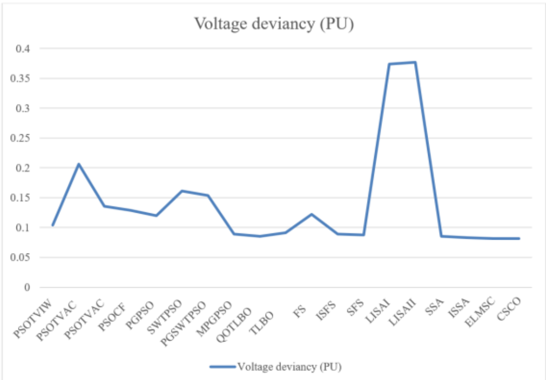

Figure 4. Appraisal of Voltage aberration (X-axis; Methods, Y-axis: value of VD in PU)

CSCO performed well in reducing the power eccentricity.

Table 3 and Figure 5 give the Power steadiness valuation and projected ELMSC, CSCO performed well in power steadiness enhancement.

Table 2. Assessment of voltage aberration

Method	Voltage deviancy (PU)
PSO-TVIW (Polprasert *et al*., 2016)	0.1038
PSOTVAC (Polprasert *et al*., 2016)	0.2064
PSOTVAC (Polprasert *et al*., 2016)	0.1354
PSOCF (Polprasert *et al*., 2016)	0.1287
PGPSO (Polprasert *et al*., 2016)	0.1202
SWTPSO (Polprasert *et al*., 2016)	0.1614
PGSWTPSO (Polprasert *et al*., 2016)	0.1539
MPGPSO (Polprasert *et al*., 2016)	0.0892
QOTLBO (Mandal and Roy, 2013)	0.0856
TLBO (Mandal and Roy, 2013)	0.0913
FS (Tran *et al*., 2019)	0.1220
ISFS (Tran *et al*., 2019)	0.0890
SFS (Duong *et al*., 2020)	0.0877
LISAI (Nagarajan *et al*., 2020)	0.374
LISAII (Nagarajan *et al*., 2020)	0.377
SSA (Tudose *et al*., 2021)	0.0854
ISSA (Tudose *et al*., 2021)	0.0831
ELMSC	0.0812
CSCO	0.0815

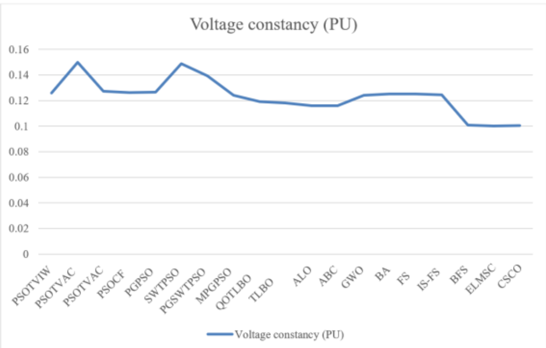

Figure 5. Assessment of voltage constancy index (X-axis; Methods, Y-axis: value of Voltage constancy in PU)

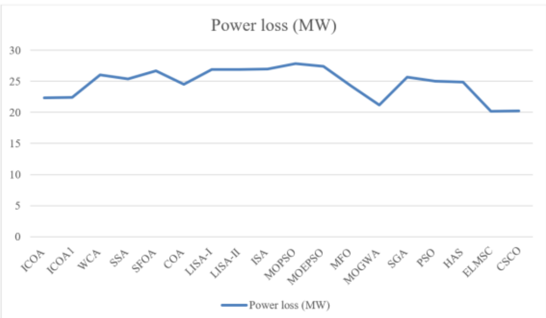

Figure 6. Appraisal of loss (X-axis; Methods, Y-axis: value of loss in MW)

Projected ELMSC and CSCO are corroborated in IEEE 57 bus system (IEEE 57-Bus Test System, n.d.). Table 4 shows the loss appraisal, Table 5 shows the voltage aberration evaluation and Table 6

Table 3. Appraisal of Voltage constancy

Method	Voltage constancy (PU)
PSOTVIW (Polprasert *et al*., 2016)	0.1258
PSOTVAC (Polprasert *et al*., 2016)	0.1499
PSOTVAC (Polprasert *et al*., 2016)	0.1271
PSOCF (Polprasert *et al*., 2016)	0.1261
PGPSO (Polprasert *et al*., 2016)	0.1264
SWTPSO (Polprasert *et al*., 2016)	0.1488
PGSWTPSO (Polprasert *et al*., 2016)	0.1394
MPGPSO (Polprasert *et al*., 2016)	0.1241
QOTLBO (Mandal and Roy, 2013)	0.1191
TLBO (Mandal and Roy, 2013)	0.1180
ALO (Mouassa *et al*., 2017)	0.1161
ABC (Mouassa *et al*., 2017)	0.1161
GWO (Mouassa *et al*., 2017)	0.1242
BA (Mouassa *et al*., 2017)	0.1252
FS (Tran *et al*., 2019)	0.1252
ISFS (Tran *et al*., 2019)	0.1245
BFS (Duong *et al*., 2020)	0.1007
ELMSC	0.1001
CSCO	0.1003

Table 4. Appraisal of power loss

Method	Power loss (MW)
ICOA (Kien *et al*., 2021)	22.376
ICOA1 (Kien *et al*., 2021)	22.383
WCA (Kien *et al*., 2021)	26.0402
SSA (Kien *et al*., 2021)	25.3854
SFOA (Kien *et al*., 2021)	26.6541
COA (Kien *et al*., 2021)	24.5358
LISA-I (Nagarajan *et al*., 2020)	26.88
LISA-II (Nagarajan *et al*., 2020)	26.92
ISA (Nagarajan *et al*., 2020)	26.97
MOPSO (Mouassa *et al*., 2019)	27.83
MOEPSO (Mouassa *et al*., 2019)	27.42
MFO (Mei *et al*., 2017)	24.25
MOGWA (Nuaekaew *et al*., 2017)	21.171
SGA (Chen *et al*., 2016)	25.64
PSO (Chen *et al*., 2016)	25.03
HAS (Chen *et al*., 2016)	24.90
ELMSC	20.189
CSCO	20.211

Table 5. Voltage aberration evaluation

Method	VD (PU)
ICOA (Kien *et al*., 2021)	0.6051
ICOA1 (Kien *et al*., 2021)	0.6155
WCA (Kien *et al*., 2021)	0.7309
SSA (Kien *et al*., 2021)	0.94
SFOA (Kien *et al*., 2021)	0.7913
COA (Kien *et al*., 2021)	0.6711
LISAI (Nagarajan *et al*., 2020)	1.0642
LISAII (Nagarajan *et al*., 2020)	1.072
ISA (Nagarajan *et al*., 2020)	1.0912
MOPSO (Mouassa *et al*., 2019)	1.10
MOEPSO (Mouassa *et al*., 2019)	0.896
ELMSC	0.6009
CSCO	0.6015

gives the power constancy assessment. Figures 6 to 8 gives the graphical appraisal between the methods.

Table 4 and Figure 6 shows the differnet values of loss obtained through various standard procedures and comparision done with the projected ELMSC and CSCO.

Table 5 and Figure 7 shows the power eccentricity evaluation and projected ELMSC, CSCO performed well in reducing the power eccentricity.

Table 6 and Figure 8 give the Power steadiness valuation and projected ELMSC, CSCO performed well in power steadiness enhancement.

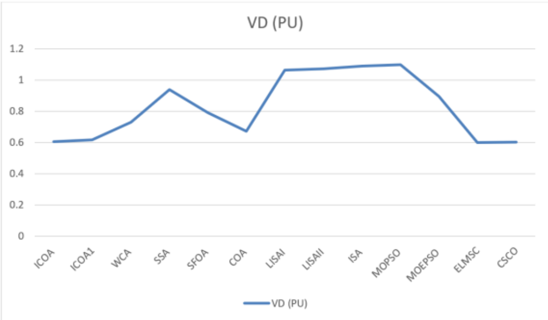

Figure 7. Appraisal of power deviance (X-axis; Methods, Y-axis: value of VD in PU)

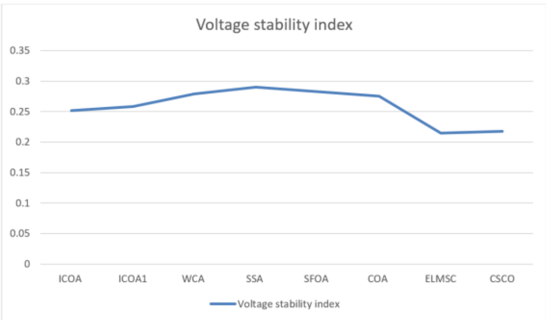

Figure 8. Appraisal of power permanence (X-axis; Methods, Y-axis: value of Voltage constancy in PU)

Table 6. Power constancy assessment

Method	Voltage stability index
ICOA (Kien *et al*., 2021)	0.25169
ICOA1 (Kien *et al*., 2021)	0.2583
WCA (Kien *et al*., 2021)	0.2789
SSA (Kien *et al*., 2021)	0.29
SFOA (Kien *et al*., 2021)	0.2831
COA (Kien *et al*., 2021)	0.2757
ELMSC	0.2145
CSCO	0.2176

Projected ELMSC and CSCO are corroborated in IEEE 118 bus system (IEEE 118-Bus Test System, n.d.). Table 7 shows the loss appraisal, Table 8 shows the voltage aberration evaluation and Table 9 gives the power constancy assessment. Figures 9 to 11 gives the graphical appraisal between the methods.

Table 7 and Figure 9 shows the differnet values of loss obtained through various standard procedures and comparision done with the projected ELMSC and CSCO.

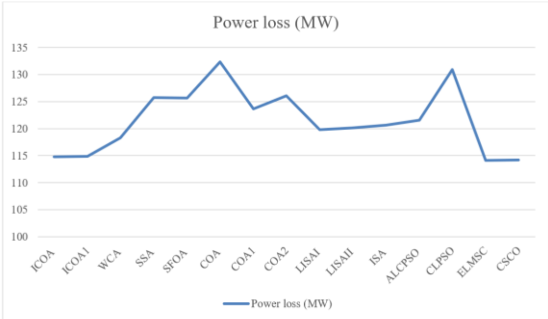

Figure 9. Appraisal of loss (X-axis; Methods, Y-axis: value of loss in MW)

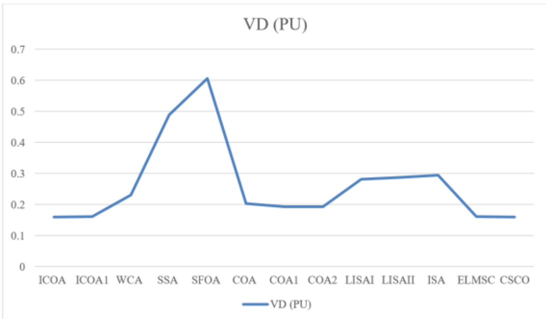

Figure 10. Appraisal of power deviance (X-axis; Methods, Y-axis: value of VD in PU)

Table 7. Loss appraisal

Method	Power loss (MW)
ICOA (Kien *et al*., 2021)	114.8036
ICOA1 (Kien *et al*., 2021)	114.8623
WCA (Kien *et al*., 2021)	118.3207
SSA (Kien *et al*., 2021)	125.7288
SFOA (Kien *et al*., 2021)	125.6801
COA (Kien *et al*., 2021)	132.3341
COA1 (Kien *et al*., 2021)	123.6867
COA2 (Kien *et al*., 2021)	126.0426
LISAI (Nagarajan *et al*., 2020)	119.79
LISAII (Nagarajan *et al*., 2020)	120.15
ISA (Nagarajan *et al*., 2020)	120.67
ALCPSO (Chen *et al*., 2016)	121.53
CLPSO (Chen *et al*., 2016)	130.96
ELMSC	114.08
CSCO	114.16

Table 8 and Figure 10 shows the power eccentricity evaluation and projected ELMSC, CSCO performed well in reducing the power eccentricity.

Table 9 and Figure 11 give the Power steadiness valuation and projected ELMSC, CSCO performed well in power steadiness enhancement.

Projected ELMSC, CSCO are corroborated in IEEE 300 bus system. Table 10 shows the loss appraisal and Table 11 shows the voltage aberration evaluation. Figures 12 and 13 give the graphical appraisal between the methods.

Table 10 and Figure 12 shows the differnet values of loss obtained through various standard procedures and comparision done with the projected ELMSC and CSCO.

Table 11 and Figure 13 shows the power eccentricity evaluation and projected ELMSC, CSCO performed well in reducing the power eccentricity.

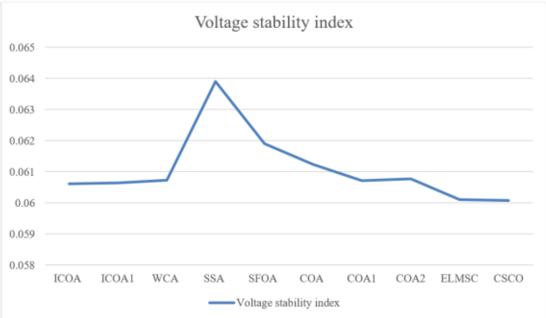

Figure 11. Appraisal of power permanence (X-axis; Methods, Y-axis: value of Voltage constancy in PU)

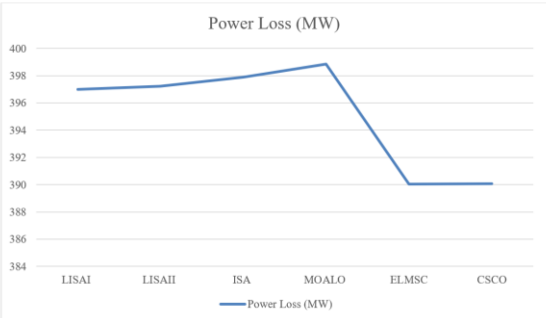

Figure 12. Appraisal of power loss (X-axis; Methods, Y-axis: value of loss in MW)

Table 8. Voltage aberration evaluation

Method	VD (PU)
ICOA (Kien *et al*., 2021)	0.1605
ICOA1 (Kien *et al*., 2021)	0.1608
WCA (Kien *et al*., 2021)	0.2315
SSA (Kien *et al*., 2021)	0.4883
SFOA (Kien *et al*., 2021)	0.6061
COA (Kien *et al*., 2021)	0.2034
COA1 (Kien *et al*., 2021)	0.1928
COA2 (Kien *et al*., 2021)	0.1936
LISAI (Nagarajan *et al*., 2020)	0.2819
LISAII (Nagarajan *et al*., 2020)	0.2876
ISA (Nagarajan *et al*., 2020)	0.2948
ELMSC	0.1611
CSCO	0.1604

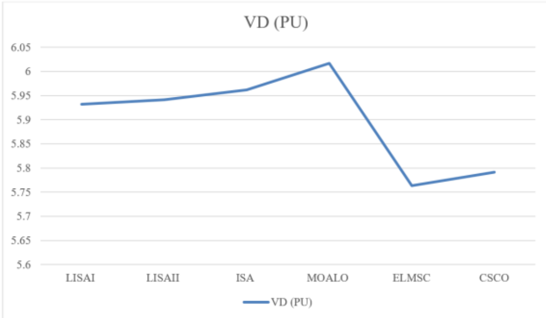

Figure 13. Appraisal of power deviance (X-axis; ethods , Y-axis: value of VD in PU)

Table 9. Power constancy assessment

Method	Voltage stability index
ICOA (Kien *et al*., 2021)	0.06061
ICOA1 (Kien *et al*., 2021)	0.06064
WCA (Kien *et al*., 2021)	0.060731
SSA (Kien *et al*., 2021)	0.0639
SFOA (Kien *et al*., 2021)	0.0619
COA (Kien *et al*., 2021)	0.06123
COA1 (Kien *et al*., 2021)	0.06072
COA2 (Kien *et al*., 2021)	0.06077
ELMSC	0.06010
CSCO	0.06008

Table 10. Loss appraisal

Method	Power Loss (MW)
LISAI (Mouassa and Bouktir, 2019)	396.983
LISAII (Mouassa and Bouktir, 2019)	397.236
ISA (Mouassa and Bouktir, 2019)	397.902
MOALO (Saravanan and Anbalagan, 2021)	398.853
ELMSC	390.041
CSCO	390.072

Table 11. Voltage aberration evaluation

Method	VD (PU)
LISAI (Nagarajan *et al*., 2020)	5.9324
LISAII (Nagarajan *et al*., 2020)	5.9416
ISA (Nagarajan *et al*., 2020)	5.9613
MOALO (Mouassa *et al*., 2019)	6.0169
ELMSC	5.7633
CSCO	5.7915

Projected ELMSC, CSCO are corroborated in IEEE 354 bus system (PSTCA, 2016; Duong *et al.*, 2020). In Table 12 shows the loss appraisal and Table 13 shows the voltage aberration evaluation. Figures 14 and 15 give the graphical appraisal between the methods.

Table 12 and Figure 14 shows the differnet values of loss obtained through various standard procedures and comparision done with the projected ELMSC and CSCO.

Table 13 and Figure 15 shows the power eccentricity evaluation and projected ELMSC, CSCO performed well in reducing the power eccentricity.

Table 14 and Figure 16 shows the time taken by IEEE 30, 57, 118, 300 and 354 bus test systems.

Conclusions

Proposed ELMSC, CSCO condensed the loss resourcefully. Candidate solutions in the projected Sphyraena Chrysotaenia optimization are Sphyraena Chrysotaenia and population in the inspection region is quixotically enthused. Spasmodically impressive solutions can be erroneous while restructuring the position of inspection agents and renewed positions may be inadequate one than the previous positions so magnificent selection is engaged. Domination comprises recurrence the self-effacing fitting solution to ensuing generation. In ELMSC initial phases of iteration, the Sphyraena Chrysotaenia Optimization Algorithm contestants are diversified in position and exponential standby generates

Table 12. Loss appraisal

Method	Power Loss (MW)
LISAI (Nagarajan *et al.*, 2020)	337.374
LISAII (Nagarajan *et al.*, 2020)	338.715
ISA (Nagarajan *et al.*, 2020)	339.325
FAHCLSO (Mouassa *et al.*, 2019)	341.001
PSO (Mouassa *et al.*, 2019)	341.123
ELMSC	336.132
CSCO	336.154

Table 13. Voltage aberration

Method	VD (PU)
LISAI (Nagarajan *et al.*, 2020)	0.4978
LISAII (Nagarajan *et al.*, 2020)	0.5117
ISA (Nagarajan *et al.*, 2020)	0.5216
FAHCLSO (Mouassa *et al.*, 2019)	0.5354
PSO (Mouassa *et al.*, 2019)	0.6395
ELMSC	0.4518
CSCO	0.4513

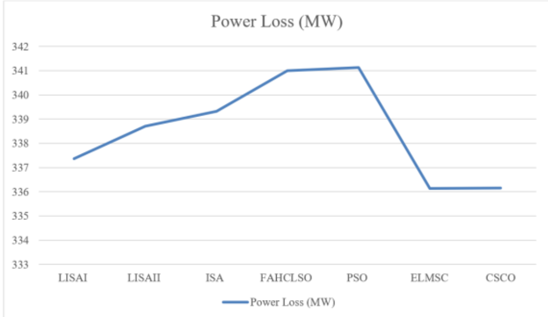

Figure 14. Appraisal of power loss (X- axis; Methods, Y-axis: value of loss in MW)

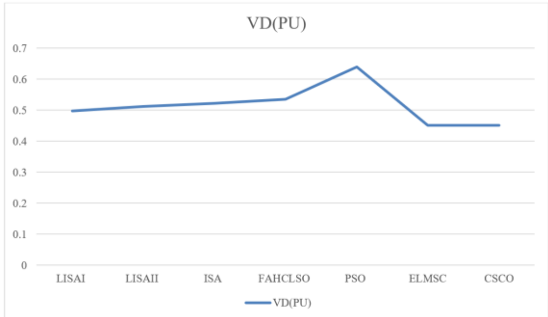

Figure 15. Appraisal of power deviance (X-axis; Methods, Y-axis: value of VD in PU)

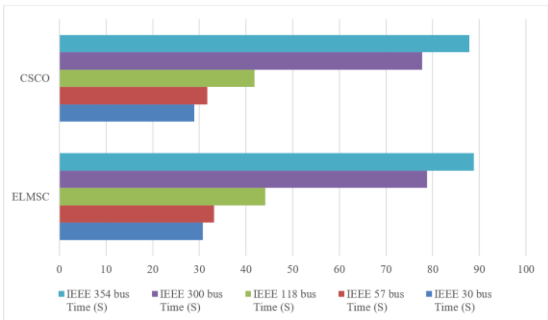

Figure 16. Time taken by ELMSC, CSCO

Table 14. Time taken by ELMSC, CSCO

Method	IEEE 30 bus Time (S)	IEEE 57 bus Time (S)	IEEE 118 bus Time (S)	IEEE 300 bus Time (S)	IEEE 354 bus Time (S)
ELMSC	30.72	33.17	44.13	78.81	88.85
CSCO	28.86	31.72	41.83	77.73	87.81

unrestricted impulsive calculations which endow the rudiments to accommodate the entire revelation area. Compatibly, all over end stage of iterations, fundamentals are enclosed by Sphyraena Chrysotaenia Optimization Algorithm contestants and all an optimal condition with equivalent scheme. Chaotic sequences are combined into the Sphyraena Chrysotaenia Optimization Algorithm (CSCO). This amalgamation will augment the Exploration and Exploitation. Tinkerbell chaotic map fabricating tenets are employed. Proposed ELMSC, CSCO are corroborated in IEEE 30, 57, 118, 300, and 354 bus test systems. For IEEE 30 bus system Real power loss obtained are ELMSC-4.3278, CSCO-4.3295. For IEEE 57 bus system Real power loss obtained are ELMSC-20.189, CSCO-20.21. For IEEE 118 bus system Real power loss obtained are ELMSC-114.08, CSCO-114.16. For IEEE 300 bus system Real power loss obtained are ELMSC-390.041, CSCO-390.072. For IEEE 354 bus system Real power loss obtained are ELMSC-336.132, CSCO-336.154. True power loss lessening, power divergence curtailing, and power constancy augmentation has been achieved.

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