

HYBRIDIZED GOLDEN MARMOSET- PEGEA CONFOEDERATA OPTIMIZATION ALGORITHM AND INTEGRATED CROSSARCHUS- LUCIHORMETICA VERRUCOSA SWARM FOR POWER LOSS REDUCTION IN ELECTRICAL TRANSMISSION AND DISTRIBUTION SYSTEM

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Abstract

Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus- Lucihormetica verrucosa Swarm optimization (ICLV) algorithm are applied to solve the real power loss reduction problem. In the Hybridized Golden marmoset- *Pegea confoederata* swarm optimization algorithm, regular attributes of the Golden marmoset is integrated with the Pegea confoederata swarm. Golden Marmoset is contingent on hereditary and societal actions in which leading entities are probable to be conquerors of the exploration area. The Pegea confoederata swarm optimization algorithm portrays the manacling and the gesticulation in the ocean. The Pegea confoederata are shining beings that forage around the biological material in the ocean and hover round in manacles. In the Integrated Crossarchus- Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm the reconnaissance for fresh embankment and searching is done concurrently and by the similar cluster of Crossarchus. By calculating the normal slumbering embankment rate in iterations, contingent on the rate of the normal slumbering embankment, the subsequent phase of the Crossarchus populace is determined. Lucihormetica verrucosa swarm optimization algorithm is integrated into the algorithm to enhance the search. HGPC and ICLV algorithms are validated in 7 benchmark functions and IEEE systems.

Keywords: Crossarchus; Golden Marmoset; Lucihormetica verrucosa; Pegea confoederata swarm

Introduction

Power loss reduction, voltage minimization, and voltage stability expansion have been achieved. Numerous methods are applied to solve the real power loss reduction problem. Many techniques; COA (Shaheen *et al.*, 2023), SAI (Varan *et al.*, 2023), EPSO (Lima *et al.*, 2023), CTO (Lenin, 2023) SARANI algorithm (Kanagasabai, 2024), Lévy-flight phasor particle swarm optimization (Gil *et al.*, 2024), JAYA algorithm (Das *et al.*, 2024a), Grasshopper Optimization Algorithm (Das *et al.*, 2024b), are applied. Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus-Lucihormetica verrucosa Swarm optimization (ICLV) algorithm are used to solve the real power loss reduction problem. In the Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC), regular attributes of the Golden marmoset is integrated with the Pegea confoederata swarm optimization algorithm by this integration exploitation ability of the procedure improved. The natural behavior of the Golden Marmoset has been imitated to design the algorithm. Primarily, the procedure starts with a populace of the arbitrary solution and searches the exploration space to discover the optimum. Golden Marmoset's lifespan comprises choosing, coupling, swapping males, and learning. Henceforth, the intellectual activities of Golden Marmoset are applied to solve the problem.

Furthermore, it also validates the activities of the Golden Marmoset. It parades their adjustable learning, hereditary, and societal deeds and how they frequently retort, rendering variations in their environs, which upholds the comprehensive order evolving from the communication of the Golden Marmoset. The fresh progenies engendered from the copulating process experience a learning procedure from the leading specific and the conditions of the surroundings. In Learning or erudition procedure the entities in the populace set can progress their appropriateness rate to grasp the leading specific set. The Pegea confoederata swarm optimization algorithm portrays the manacling and the gesticulation in the ocean. The Pegea confoederata are shining beings that forage round the biological material in the ocean and hover round in manacles. The control factor is used to passage the process between exploration and exploitation. In the Integrated Crossarchus- Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm, regular activities of Crossarchus are emulated to design the algorithm, and Lucihormetica Verrucosa Swarm has been integrated into the procedure. The Crossarchus won't seizure big prey stuff, which might deliver

sustenance for the entire cluster. By calculating the normal slumbering embankment rate in iterations, contingent on the rate of the normal slumbering embankment, the subsequent phase of the Crossarchus populace is determined. The quantity of child-minders depends on the populace size; they mark the procedure by tumbling the entire populace size based on the percentage set. Lucihormetica verrucosa swarm optimization algorithm is integrated into the algorithm to enhance the search. As soon as Lucihormetica verrucosa is voracious in the interim phase, it wanders from its contented lodging and associates establishment to gaze for nutrition. A fractional disparity equation designs the starvation approach.

Mathematical Design

The main objective function of the problem is demarcated as,

$$\text{Min } \tilde{F}(\bar{g}, \bar{h}) \quad (1)$$

$$g = [VL_{G1}, \dots, VL_{GNg}; QC_1, \dots, QC_{Nc}; T_1, \dots, T_{Nr}]$$

$$h = [PG_{slack}; VL_1, \dots, VL_{NLoad}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{Nr}]$$

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

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

$$F_3 = \text{Minimize } L_{Maximum}$$

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

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

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

Equality constraints,

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

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

Inequality constraints,

$$P_{gsi}^{\min} \leq P_{gsi} \leq P_{gsi}^{\max} \quad (2)$$

Reactive power generation (QGi)

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (3)$$

Load bus voltage (VLi)

$$VL_i^{\min} \leq VL_i \leq VL_i^{\max}, i \in N_L \quad (4)$$

Transformers tap setting (Ti)

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (5)$$

Switchable reactive power compensations (QCi)

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_C \quad (6)$$

$$|SL_i| \leq S_{L_i}^{\max}, i \in N_{TL} \quad (7)$$

Generator bus voltage (VGi)

$$VG_i^{\min} \leq VG_i \leq VG_i^{\max}, i \in N_g \quad (8)$$

$$F = F_1 + r_1 F_2 + u F_3 = F_1 + \left[\sum_{i=1}^{N_L} x_v [VL_i - VL_i^{\min}]^2 + \sum_{i=1}^{N_G} r_g [QG_i - QG_i^{\min}]^2 \right] + r_f F_3 VL_i^{\text{minimum}} = \begin{cases} VL_i^{\max}, & VL_i > VL_i^{\max} \\ VL_i^{\min}, & VL_i < VL_i^{\min} \end{cases} \quad (9)$$

$$QG_i^{\text{minimum}} = \begin{cases} QG_i^{\max}, & QG_i > QG_i^{\max} \\ QG_i^{\min}, & QG_i < QG_i^{\min} \end{cases} \quad (10)$$

Hybridized Golden Marmoset - Pegea Confoederata Swarm Optimization Algorithm

In the Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC), regular attributes of the Golden marmoset are integrated with the Pegea confoederata swarm optimization algorithm. An inertia weight included in the rapid approach of *Lucihormetica verrucosa* is united in the process to enhance the rapidity of the search. Primarily, the procedure starts with a populace of the arbitrary solution and searches the exploration space to discover the optimum. The lifespan of Golden Marmoset (Raboy *et al.*, 2004) comprises choosing, coupling, swapping males, and learning. Furthermore, it also validates the activities

of the Golden Marmoset. It parades their adjustable learning, hereditary, and societal deeds and how they frequently retort, rendering variations in their environs, which upholds the comprehensive order evolving from the communication of the Golden Marmoset. In the state space exemplary, the female and male Golden Marmoset are defined as follows,

$$GMMT^{**} = -\alpha GMMT^{*} + \gamma_1 Sub - \text{Mature male} \quad (11)$$

$GMMT^{*} \rightarrow$ Mature male Golden Marmoset
 $\beta, \gamma_1 \rightarrow$ variable(state)

$Sub -$ Mature defines the stage of male Golden Marmoset is semi - matured level

$$GMFT^{**} = -\alpha GMFT^{*} + \gamma_2 Sub. \text{Mature female} \quad (12)$$

$GMFT^{*} \rightarrow$ Mature female Golden Marmoset

$\alpha, \beta \rightarrow$ decrease degree

$\delta_2 \rightarrow$ specify the variable(state)

$Sub. \text{Mature} \rightarrow$

Golden Marmoset is semi. matured level

$$Sub. \text{Mature male} GM^{*} = \delta_1 SGMFT^{*}$$

$$-\gamma_1 Sub. \text{Mature male} GM - \alpha Sub. \text{Mature male} GM \quad (13)$$

$SGMFT^{*} \rightarrow$ Adolescent male Golden Marmoset

$$Sub. \text{Mature female} GM^{*} = \delta_2 SGMFT^{*}$$

$$-\gamma_2 Sub. \text{Mature female} GM -$$

$$\alpha Sub. \text{Mature female} GM \quad (14)$$

$SGMFT^{*} \rightarrow$ Adolescent female Golden Marmoset

$$Adolescent \text{ male } GM^{*} = \varepsilon_1 NT^{*} - \delta_1 SGMFT^{*} - \alpha SGMFT^{*}$$

$NT^{*} \rightarrow$ Nursling male Golden Marmoset

$$Adolescent \text{ female } GM^{*} = \varepsilon_2 NLT^{*} -$$

$$\delta_2 SGMFT^{*} - \alpha SGMFT^{*}$$

$NLT^{*} \rightarrow$ Nursling

female Golden Marmoset

$$NT^{*} = \eta_1 GMMT^{*} + \mu_1 GMFT^{*} - \varepsilon_1 NT^{*} - \beta NT^{*} \quad (15)$$

$$NLT^{*} = \eta_2 GMMT^{*} + \mu_2 GMFT^{*} - \varepsilon_2 NLT^{*} - \beta NLT^{*} \quad (16)$$

$$\eta_1 = 2.0/3.0 \mu_1$$

$$\eta_2 = 2.0/3.0 \mu_2$$

In the embryonic of the Golden Marmoset, the examination agents are divided into twofold categories, recognized as the Male and Female Golden Marmoset. The populace of Golden

Marmoset in clusters and entities in the cluster is defined as,

$P \rightarrow \text{population}$

$C_i \rightarrow \text{cluster}$

$i = 1, 2, 3, \dots, C$

$P = \{GMMT^*_{j}\} \cup \{GMFT^*_{k}\}$

$GMMT^*_{j} \rightarrow \text{male Golden Marmoset}$

$GMFT^*_{k} \rightarrow \text{female Golden Marmoset}$

$j = 1, 2, 3, \dots, GMMT^*_{size}$

$k = 1, 2, 3, \dots, GMFT^*_{size}$

$C_i \supset GMMT^*, GMFT^*$

$GMMT^* \neq GMFT^*$

$GMMT^*_{size} = \text{Base} [0.90 - R(0.250, 0.40)] * |C_i|$

$GMFT^*_{size} = \text{Base} [0.90 - R(0.450, 0.60)] * |C_i|$

$GMMT^*_{size} + GMFT^*_{size} = \text{ActualGM}_{size}$

$\text{ActualGM}_{size} \in \mathbb{H}^*$

Golden Marmoset is contingent on hereditary and societal actions in which leading entities are probable to be conquerors of the exploration area. Appropriateness assessment forecasts the possibility and endurance degree of the specific to be transported to the subsequent generation of the populace and is demarcated as follows,

$\text{Min } O(\mathfrak{U})$ (17)

$\mathfrak{U} \in \mathbb{H}$

$\mathfrak{U}_i = (\mathfrak{U}_1, \mathfrak{U}_2, \dots, \mathfrak{U}_z)$

$\mathfrak{U}$ specify the entity

$\mathbb{H}$ indicate the specific feasible area in the exploration region

O is the optimal value

The elementary assembly of the Golden Marmoset charts the leading pyramid where the advanced grade entities govern the enduring inferior grade entities in the cluster. Entities are segmented into advanced grade or non-ruled entities and inferior grade or conquered entities. Consequently, the specific grade is grounded on the appropriateness rate. The preeminent specific in the cluster is recognized as the α entity. Then, α male Golden Marmoset is the finest male Golden Marmoset, and α Female Golden Marmoset is the preeminent female Golden Marmoset specific in the cluster. These are signified as,

$GMMT^*_i = \min\{O(\mathfrak{U}_j) | j \in \{\text{MaleGM}\}_i, i \in \{C_i\}\}$ (18)

$GMFT^*_i = \min\{O(\mathfrak{U}_j) | j \in \{\text{FemaleGM}\}_i, i \in \{C_i\}\}$

$GMMT^*_i$ and $GMFT^*_i$ are the confined (local) optima

$GMMT^*_i, GMFT^*_i \in \mathbb{Z}$

[global best male GM, global best female GM] =

$\min\{GMMT^*, GMFT^*\}$

$\mathfrak{U}, \mathfrak{U}^* \in \{\text{Male GM}\}$ then =
 $\begin{cases} \mathfrak{U} \in \{\text{Leading Entity}(LE)\}, \text{if } O(\mathfrak{U}) > O(\mathfrak{U}^*) \\ \mathfrak{U}^* \in \{(LE)\}, \mathfrak{U} \in \{\text{non leading entity}(NLE)\}, \\ \text{otherwise} \end{cases}$

$\mathfrak{U}, \mathfrak{U}^* \in \{\text{Female GM}\}$ then =

$\begin{cases} \mathfrak{U} \in \{NLE\}_{\text{Female}}, \text{if } O(\mathfrak{U}) > O(\mathfrak{U}^*) \\ \mathfrak{U}^* \in \{NLE\}_{\text{Female}}, \mathfrak{U} \in \{LE\}, \text{otherwise} \end{cases}$

Precisely, the selection procedure is contingent only on a leading specific, this tip to local optimum and decrease populace multiplicity.

$\mathfrak{U}$ of female Golden Marmoset =

$\text{Copulating}(\mathfrak{U}^{GMMT^*}, \mathfrak{U}^{GMFT^*})$ (19)

$\mathfrak{U}^{GMMT^*}, \mathfrak{U}^{GMFT^*} \in C_i$

The age of nursing male and Female Golden Marmoset is fixed at Zero; at that time experience an erudition procedure to progress their appropriateness degree. The progenies engendered in every. $\{C_i\}$ from the copulating procedure touches sexual adulthood $\mathcal{B}$.

$\mathfrak{U}^{NT^*} = \begin{cases} \mathfrak{U}^{NT^*} \in \{SGMFT^*\}, \text{if age} = \text{one} \\ \mathfrak{U}^{NT^*} \in \{NT^*\}, \text{otherwise} \end{cases}$ (20)

$SGMFT^* \rightarrow \text{Adolescent male Golden Marmoset}$

$\mathfrak{U}^{SGMFT^*} = \begin{cases} \mathfrak{U}^{SGMFT^*} \in \{SGMMT^*\}, \text{if age} = \text{four} \\ \mathfrak{U}^{SGMFT^*} \in \{SGMFT^*\}, \text{otherwise} \end{cases}$ (21)

$SGMMT^* \rightarrow \text{Sub. Mature male Golden Marmoset}$

$\mathfrak{U}^{NLT^*} = \begin{cases} \mathfrak{U}^{NLT^*} \in \{SGMFT^*\}, \text{if age} = \text{one} \\ \mathfrak{U}^{NLT^*} \in \{NLT^*\}, \text{otherwise} \end{cases}$ (22)

$SGMFT^* \rightarrow \text{Adolescent female Golden Marmoset}$

$\mathfrak{U}^{SGMFT^*} = \begin{cases} \mathfrak{U}^{SGMFT^*} \in \{SGMFT^*\}, \text{if age} = \text{three} \\ \mathfrak{U}^{SGMFT^*} \in \{SGMFT^*\}, \text{otherwise} \end{cases}$ (23)

$SGMFT^* \rightarrow \text{Sub. Mature female Golden Marmoset}$

$\mathfrak{U}^{SGMFT^*} = \begin{cases} \mathfrak{U}^{SGMFT^*} \in \{GMFT^*\}, \text{if age} = \text{five} \\ \mathfrak{U}^{SGMFT^*} \in \{SGMFT^*\}, \text{otherwise} \end{cases}$ (24)

The fresh progenies engendered from the copulating process experience a learning procedure from the leading specific and the conditions of the surroundings. Rendering to the appropriateness degree of the wandering male Golden Marmoset, the interchange stratagem disparity plays out in a dissimilar method. The male Golden Marmoset interchange can be demarcated as,

$MI = \begin{cases} \text{Interchange}(\mathfrak{U}_{WGMMT^*}, \mathfrak{U}_{GMMT^*}), \\ \text{if } O(\mathfrak{U}_{WGMMT^*}) > O(\mathfrak{U}_{GMMT^*}) \\ \mathfrak{U}_{WGMMT^*} \in \{\text{Abolition Set (AS)}\}, \\ \text{otherwise} \end{cases}$ (25)

$\mathcal{W}_{GMMT*} \rightarrow$ wandering male

Golden Marmoset

$MI \rightarrow$ male Golden Marmoset interchange

$\exists \mathcal{W}_{GMMT*} \in C_i \parallel \mathcal{W}_{GMMT*} \in \{LE\}_{GMMT*} : (\mathcal{W}_{GMMT*} \in \{C_j\}_{j=1, \dots, GMMT*}) \mid i \neq j,$

In the Learning or erudition procedure the entities in the populace set can progress their appropriateness rate to grasp the leading specific set. Exploration is attained by the learning technique, which augments a specific's appropriateness and achieves the optimum solution. The learning technique is smeared to the Golden Marmoset algorithm to accomplish the preferred outcomes in comprehensive optima, and this can be signified as,

$$LP = \{P, \mathbb{H}, \delta, LP(\mathcal{W}), O(\mathcal{W}), \mathbb{Z}\} \quad (26)$$

$LP \rightarrow$ Learning or erudition procedure

$P \rightarrow$ population

$\mathbb{H} \rightarrow$ specific feasible

area in the exploration region

$\delta \rightarrow$ degree of erudition $\in (0 \leq \delta \leq 1)$

$O(\mathcal{W}) \rightarrow$ appropriateness rate

$\mathbb{Z} \rightarrow$ region of the problem

$LP(\mathcal{W}_k, i, j) : \forall \mathcal{W} \in \mathbb{H} \mid \exists z \in \mathbb{Z}$

Pegea confoederata swarm optimization algorithm portrays the manacling and the gesticulation in the ocean. The Pegea confoederata are shining beings that forage round the biological material in the ocean and hover round in manacles. These actions everywhere the manacle associates ascribe as a lengthy manacle are depicted in the Pegea confoederata swarm optimization algorithm. The process of Pegea confoederata when rummaging in oceans has been emulated to design the Pegea confoederata swarm optimization algorithm, and the Location of the lead Pegea confoederata will be altered as follows,

$$Pc_j^1 = \begin{cases} E_j + a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 \geq 0.5 \\ E_j - a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 < 0.5 \end{cases} \quad (27)$$

Pc_j^1 location of lead Pegea confoederata

E_j is nutrition location

$\max_j, \min_j$ are the maximum and minimum limits

a_1, a_2 and a_3 are arbitrary numbers

$$a_1 = 2e^{-\left(-\frac{4t}{T}\right)^2}$$

where t is current iteration

T is maximum number of iteration

a_1, a_2 and $a_3 \in [0, 1]$

$$Pc_j^i = \frac{1}{2} uw^2 + x_o w$$

Where $i \geq 2.0$; $u = \frac{x_F}{x_o}$; $Pc = \frac{Pc - Pc_o}{w}$

$$Pc_j^i = \frac{1}{2} (Pc_j^i + Pc_j^{i-1})$$

$$Pc_j^i = \begin{cases} \Delta \cdot E_j + a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 \geq 0.5 \\ \Delta \cdot E_j - a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 < 0.5 \end{cases} \quad (28)$$

$$Pc_j^i = \frac{1}{2} (Pc_j^i + \Delta \cdot Pc_j^{i-1})$$

$$Pc_j^i = \begin{cases} 1 & \text{if } Z_{ij} > 0.50 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Fit} = \partial \text{Er}(D) + \varphi \frac{|F|}{|T|}$$

To avoid the error in data distribution about nutrition location till the culmination of the manacle, the Bounce acquaintances, which are enthused from the neural networks, are integrated. Odd and even Pegea confoederata are modernized by fresh altered chief Location and the adapted supporter location with the entrenched encompassing factor and twofold neighbor supervision appraisal.

$$\text{centre point}_j^i = 1 / \sqrt{2(\Delta \cdot Pc_j^{i-1} + \Delta \cdot Pc_j^{i+1})}; \quad i \% 2 == 0 \quad (29)$$

$$\text{swiftness}_j^i = \text{abs}(\text{centre point}_j^i + Pc_j^i); \quad i \% 2 == 0 \quad (30)$$

$$Pc_j^i = \text{centre point}_j^i - \text{swiftness}_j^i; \quad i \% 2 == 0 \quad (31)$$

Pegea confoederata swarm optimization algorithm starts akin to the universal optimal by originating manifold Pegea confoederata with arbitrary locations.

Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC)

- Start
- Parameters are initialized
// Golden Marmoset algorithm//
- Categorize the exploration agents
- $GMMT^* = -\alpha GMMT^* + \gamma_1 \text{Sub} - \text{Mature male}$
- $GMFT^* = -\alpha GMFT^* + \gamma_2 \text{Sub. Mature female}$
- $SGMMT^* = \delta_1 SGMMT^* - \gamma_1 \text{Sub. Mature maleGM} - \alpha SGMMT^*$
- $SGMFT^*$ is the Adolescent male
Golden Marmoset
- $SMF GM^* = \delta_2 SGMFT^* - \gamma_2 \text{Sub. Mature femaleGM} - \alpha SGMFT^*$
- $AM GM^* = \varepsilon_1 NT^* - \delta_1 SGMFT^* - \alpha SGMFT^*$

- j. $AF\ GM^* = \varepsilon_2 NLT^* - \delta_2 SGMFT^* - \alpha SGMFT^*$
- k. $NT^* = \eta_1 GMMT^* + \mu_1 GMFT^* - \varepsilon_1 NT^* - \beta NT^*$
- l. $NLT^* = \eta_2 GMMT^* + \mu_2 GMFT^* - \varepsilon_2 NLT^* - \beta NLT^*$
- m. $GMMT_i = \min\{O(\mathcal{U}_j | j \in \{MaleGLT\}_i, i \in \{C_i\})\}$
- n. $GMFT_i = \min\{O(\mathcal{U}_j | j \in \{FemaleGLT\}_i, i \in \{C_i\})\}$
- o. Choose the best entity form α - male and female Golden Marmoset.
- p. $\begin{bmatrix} \text{global best male GM}, \\ \text{global best female GM} \end{bmatrix} = \min\{\{GMMT^*\}, \{GMFT^*\}\}$
- q. Split the entities: leading and non-leading
- r. $\mathcal{U}, \mathcal{U}^* \in \{Male\ GM\}$ then =
$$\begin{cases} \mathcal{U} \in \{Leading\ Entity(LE)\}, \\ \quad \text{if } O(\mathcal{U}) > O(\mathcal{U}^*) \\ \mathcal{U}^* \in \{(LE)\}, \\ \mathcal{U} \in \{non\ leading\ entity(NLE)\}, \\ \quad \text{otherwise} \end{cases}$$
- s. $\mathcal{U}, \mathcal{U}^* \in \{Female\ GM\}$ then =
$$\begin{cases} \mathcal{U} \in \{NLE\}_{Female}, \text{ if } O(\mathcal{U}) > O(\mathcal{U}^*) \\ \mathcal{U}^* \in \{NLE\}_{Female}, \mathcal{U} \in \{LE\}, \text{ otherwise} \end{cases}$$
- t. Apply the copulating process and engender progenies.
- u. $\mathcal{U}$ of female Golden Marmoset = Copulating($\mathcal{U}^{GMMT^*}, \mathcal{U}^{GMFT^*}$)
- v. $\mathcal{U}^{NT^*} = \begin{cases} \mathcal{U}^{NT^*} \in \{SGMFT^*\}, \text{ if age = one} \\ \mathcal{U}^{NT^*} \in \{NT^*\}, \text{ otherwise} \end{cases}$
- w. $\mathcal{U}^{SGMFT^*} = \begin{cases} \mathcal{U}^{SGMFT^*} \in \{SGMFT^*\}, \\ \quad \text{if age = four} \\ \mathcal{U}^{SGMFT^*} \in \{SGMFT^*\}, \\ \quad \text{otherwise} \end{cases}$
- x. $\mathcal{U}^{NLT^*} = \begin{cases} \mathcal{U}^{NLT^*} \in \{SGMFT^*\}, \\ \quad \text{if age = one} \\ \mathcal{U}^{NLT^*} \in \{NLT^*\}, \text{ otherwise} \end{cases}$
- y. $\mathcal{U}^{SGMFT^*} = \begin{cases} \mathcal{U}^{SGMFT^*} \in \{SGMFT^*\}, \\ \quad \text{if age = three} \\ \mathcal{U}^{SGMFT^*} \in \{SGMFT^*\}, \\ \quad \text{otherwise} \end{cases}$
- z. $\mathcal{U}^{SGMFT^*} = \begin{cases} \mathcal{U}^{SGMFT^*} \in \{GMFT^*\} \\ \quad \text{, if age = five} \\ \mathcal{U}^{SGMFT^*} \in \{SGMFT^*\} \\ \quad \text{, otherwise} \end{cases}$
- aa. Compute the appropriateness rate of progenies'
- bb. Wandering male Golden Marmosets find an appropriate cluster to interchange with the leading male.
- cc. $MI = \begin{cases} \text{Interchange}(\mathcal{U}_{WGMMT^*}, \mathcal{U}_{GMMT^*}), \\ \quad \text{if } O(\mathcal{U}_{WGMMT^*}) > O(\mathcal{U}_{GMMT^*}) \\ \mathcal{U}_{WGMMT^*} \in \{Abolition\ Set\ (AS)\}, \\ \quad \text{otherwise} \end{cases}$
- dd. Apply the Learning procedure.
- ee. $LP = \{P, \mathbb{H}, \delta, LP(\mathcal{U}), O(\mathcal{U}), \mathbb{Z}\}$
- ff. $P = \{GMMT^*_j\} \cup \{GMFT^*_k\}$
- // Pegea confoederata algorithm//
- gg. Initialize the Population of Pegea confoederata illogically
- hh. The fitness value of Pegea confoederata is calculated
- ii. Nutrition E = excellent fitness
- jj. For each i in Pegea confoederata Pc_i
- kk. if ($i \% 2 == 1$); then
- ll. Update the chief Location
- mm. $pc_j^1 = \begin{cases} \Delta \cdot E_j + a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 \geq 0.5 \\ \Delta \cdot E_j - a_1 ((\max_j - \min_j)a_2 + \min_j) & a_3 < 0.5 \end{cases}$
- nn. End if
- oo. End for
- pp. For each i in Pegea confoederata Pc_i
- qq. if ($i == final$ Pegea confoederata) then
- rr. Modernize the Location
- ss. $Pc_j^i = \frac{1}{2} uw^2 + x_o w$
- tt. Else if ($i \% 2 == 0$ & & $i!$ = final Pegea confoederata)
- uu. Comput the centre point $point_j^i$
- vv. centre point $point_j^i = 1/2(\Delta \cdot Pc_j^{i-1} + \Delta \cdot Pc_j^{i+1})$; $i \% 2 == 0$
- ww. Calculate the swiftness j^i
- xx. swiftness $j^i = abs(\text{centre point}_j^i + Pc_j^i)$; $i \% 2 = 0$
- yy. Modernize the supporter location
- zz. $Pc_j^i = \text{centre point}_j^i - \text{swiftness}_j^i$; $i \% 2 == 0$
- aaa. Relocate the Pegea confoederata, which crossed the boundaries
- bbb. Return the best solution
- ccc. End

Integrated Crossarchus -Lucihormetica Verrucosa Swarm Optimization Algorithm

In the Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm, regular activities of Crossarchus are emulated to design the algorithm, and Lucihormetica Verrucosa Swarm has been integrated into the procedure. Natural actions of Crossarchus (Dunham *et al.*, 2003) are imitated to design the Crossarchus algorithm. The Crossarchus won't seizure big prey stuff, which might deliver sustenance for the entire cluster. The non-appearance of a slaughter morsel and concentrated carton stalking has caused the Crossarchus to espouse a communal construction that permits each associate to search and consume itself with multiple movements. The itinerant

performance averts more than the required exploitation of a specific zone, and it also guarantees exploration of the entire terrain since no beforehand stayed slumbering embankment is reverted. Initialization of the Crossarchus optimization algorithm starts with the engendering of the candidate solution as follows,

$$C = \begin{bmatrix} c_{1,1} & \cdots & c_{1,d} \\ \vdots & \ddots & \vdots \\ c_{n,1} & \cdots & c_{n,d} \end{bmatrix} \quad (32)$$

$c \rightarrow$ present set of candidate population
 $c_{i,j} = U[UB, LB, size]$
 $UB, LB \rightarrow$ upper and lowerbound limits
 U is Uniform distribution number

The recompense performance version comprises restriction of prey magnitude, communal association, seminomadic lifecycle, etc. In this paper, Crossarchus communal assemblies are dominant pathfinders and child-minders. Every cluster underwrites to the recompense performance version, which clues to a seminomadic method of lifecycle in a terrain hugely sufficient to care for the complete cluster. This itinerant performance averts more than the required exploitation of a specific zone, and it also guarantees exploration of the entire terrain since no beforehand stayed slumbering embankment is reverted. As soon as the populace is engendered, the appropriateness rate for each solution is calculated. The prospect rate of populace fitness is premeditated. Then, the dominant female Crossarchus is selected as,

$$\beta = \text{Fitness}_i / \sum_{i=1}^n \text{fitness}_i \quad (33)$$

$\beta \rightarrow$ dominant female Crossarchus
 The quantity of Crossarchus in the dominant cluster links to $n - cm$.
 where cm is child – minders

The dominant female Crossarchus guidance preserves the family inside a route symbolized by gawp. The preliminary slumbering embankment is set to ϕ , and every Crossarchus slumber in it. To create a candidate sustenance location, the Crossarchus optimization algorithm uses the expression as follows,

$$C_{i+1} = C_i + O * \text{Gawp} \quad (34)$$

$$O \in [-1, 1]$$

$$\text{slumbering embankment} = \frac{\text{Fit}_{i+1} - \text{Fit}_i}{\text{maximum}\{\text{Fit}_{i+1}, \text{Fit}_i\}}$$

The normal rate of the slumbering embankment is defined as,

$$\delta = \frac{\sum_{i=1}^n \text{slumbering embankment}_i}{n} \quad (35)$$

The procedure transfers to the pathfinder stage, where the succeeding sustenance spring or slumbering embankment is estimated as soon as the child-minder interchange standard is encountered. The pathfinder's guise for the succeeding slumbering embankment since the Crossarchus is acknowledged not to reoccurrence to the preceding slumbering embankment, which assurances exploration. The pathfinding is completed concurrently with searching. This drive is sculpted as a comprehensive victory or catastrophe assessment of discovering a fresh slumbering embankment. In supplementary verses, this drive is contingent on the complete enactment of the Crossarchus. The basis is that if the clan searches far-adequate, they will determine a fresh slumbering embankment.

$$C_{i+1} = \begin{cases} C_i - A * O * R * [C_i - \vec{P}] & \text{if } \delta_{i+1} > \delta_i ; [\text{Exploration}] \\ C_i + A * O * R * [C_i - \vec{P}] & \text{Else ; } [\text{Exploitation}] \end{cases} \quad (36)$$

$$R \in [0, 1]$$

$$A = (1 - \text{iter}/\text{max.iter})^{(2 * \text{iter}/\text{max.iter})}$$

$$\vec{P} = \sum_{i=1}^n C_i * \text{slumbering embankment}_i / C_i$$

$$A \& \vec{P} \rightarrow$$

the drive level of rossarchus rendering to Crossarchus

The child-minders are generally the subsidiary cluster associates that endure with the young Crossarchus and are swapped recurrently to permit the dominant female Crossarchus to clue the remnants of the cluster on everyday searching.

Lucihormetica verrucosa swarm optimization algorithm is integrated into the algorithm to enhance the search. In the algorithm, basic movement actions of Lucihormetica verrucosa (Vršanský *et al.*, 2012) are imitated to formulate the algorithm. Rush Teeming approach of Lucihormetica verrucosa is defined as Implement.

$$L_i = \begin{cases} L_i + P * R * (O_i - L_i), O_i \neq L_i \\ L_i + P * R * (O_g - L_i), O_i = L_i \end{cases} \quad (37)$$

$L_i \rightarrow$ location of Lucihormetica verrucosa

P define the phase

$$R \in [0, 1]$$

$O_i, O_g \rightarrow$ personal and global best positions

$$O_i = U_j\{L_j, |L_i - L_j| \leq V\} \quad (38)$$

where V is vision; $i, j = 1, 2, 3, \dots, N$
 $O_g = U_i[L_i]$

The scattering approach of Lucihormetica verrucosa is defined as,

$$L_i = L_i + R * (1, D) \quad (39)$$

$D \rightarrow$ dimension
 $R \in [0, 1]$

The hard-nosed approach of Lucihormetica verrucosa is defined as,

$L_k = O_g$
 where $k \in [1, N]$
 $O_i, O_g \rightarrow$ personal and global best position

An inertia weight included in the Rush Teeming approach of Lucihormetica verrucosa and is defined as,

$$L_i = \begin{cases} \omega * (L_i + P * R * (O_i - L_i)), & O_i \neq L_i \\ \omega * (L_i + P * R * (O_g - L_i)), & O_i = L_i \end{cases} \quad (40)$$

$\omega \rightarrow$ inertia weight

As soon as Lucihormetica verrucosa is voracious in the interim phase, it wanders from its contented lodging and associates establishment to gaze for nutrition. A fractional disparity equation designs the starvation approach. Lucihormetica verrucosa wanders from lodging to any accessible nutrition spring inside the exploration region. An onset of starvation is demarcated. As soon as Lucihormetica verrucosa is starving and onset starvation is touched; it wanders to nutrition spring. The starvation approach averts local optima and augments the multiplicity of the populace. The fractional disparity equation is defined as,

$$\frac{\partial z}{\partial t} = -Q \frac{\partial z}{\partial L} \quad (41)$$

$Q \rightarrow$ control the rapidness of the passage
 $z(0, L) = z_0(L)$
 $t \rightarrow$ period
 $z(0, L) = z_0(L) \rightarrow$ preliminary distribution
 $z(t, L) \rightarrow$ size of the population
 $\frac{\partial z}{\partial t} + Q \frac{\partial z}{\partial L} = 0$
 $\frac{dz}{dt} = \frac{dL}{Q} = \frac{dz}{0}$
 $dL - Qdt = 0$
 $L - Qt = \beta$
 $z = z(\beta)$
 $z = z(L - Qt)$
 $z[t, L] = z_0[-Qt + L]$

Starvation approach of Lucihormetica verrucosa is defined as,

$$L_i = L_i + (L_i - Qt) + L_{\text{nutrition}} \quad (42)$$

$(L_i - Qt)$ specify the passage form current location

Food-searching capability enhancement is defined as follows,

$$s_{i,j}^{SB_1} = \begin{cases} s_{i,j} + R * (Food_j - U * s_{i,j}), & \text{if } O_{SB} < O_i \\ s_{i,j} + R * (s_{i,j} - Food_j), & \text{Else} \end{cases} \quad (43)$$

$s_{i,j}^{SB_1} \rightarrow$ location of Lucihormetica verrucosa

Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm

- a. Start
- b. Set the parameter values
- c. Engender the Crossarchus population
- d. Create the number of child-minders
- e. Fix $n = n - cm$
- f. Fix the child-minders interchange factor
- g. For $iter = 1: \text{max.iter}$
- h. Compute the fitness rate of Crossarchus
- i. Define the Dominant Crossarchus
- j. $\beta = \text{Fitness}_i / \sum_{i=1}^n \text{fitness}_i$
- k. Engender candidate sustenance location
- l. $C_{i+1} = C_i + O * \text{Gawp}$
- m. Compute the fresh fitness value. C_{i+1}
- n. // Employ Lucihormetica verrucosa swarm //
- o. Fix $O_g = L_1$
- p. For $i = \text{two to } N$ do
- q. if $f(L_i) < f(O_g)$, then
- r. $L_i = O_g$
- s. For $t = \text{one to } T$. Maximum do
- t. For $i = \text{one to } N$ do
- u. For $j = \text{one to } N$ do
- v. if $\text{abs}(|L_i - L_j| \leq V); f(L_i) < f(L_j)$, then
- w. $L_i = O_j$
- x. End if
- y. End for
- z. if $L_i == O_i$, then
- aa. $L_i = \omega * (L_i + P * R * (O_i - L_i))$
- bb. Otherwise
- cc. $L_i = \omega * (L_i + P * R * (O_g - L_i))$
- dd. End if
- ee. if $f(L_i) < f(O_g)$, then
- ff. $L_i = O_g$
- gg. End if
- hh. End for

ii. if Starvation == $t_{\text{Starvation}}$, then
 jj. $L_i = L_i + (L_i - Qt) + L_{\text{nutrition}}$
 kk. Starvation_i = 0
 ll. Increase the count of Starvation_i
 mm. end if
 nn. For $i = \text{one to } N$ do
 oo. $L_i = L_i + R * (1, D)$
 pp. if $f(L_i) < f(O_g)$, then
 qq. $L_i = O_g$
 rr. End if
 ss. End for
 tt. $k = R * \text{int}(1, N)$
 uu. $L_k = O_g$
 vv. end for
 ww. Estimate the slumbering embankment.
 xx. slumbering embankment =

$$\frac{\text{Fitness}_{i+1} - \text{Fitness}_i}{\text{maximum}\{\text{Fitness}_{i+1}, \text{Fitness}_i\}}$$

 yy. Calculate the normal rate of
 slumbering embankment
 zz. $\delta = \frac{\sum_{i=1}^n \text{slumbering embankment}_i}{n}$
 aaa. Compute the drive of Crossarchus
 bbb. $\vec{P} = \sum_{i=1}^n C_i * \text{slumbering embankment}_i / C_i$
 ccc. Interchange the child – minders;
 if counter $\geq$ interchange factor
 ddd. Engender the child-minders position
 eee. Compute the fitness value.
 fff. $\text{Fitness}_i \leq \beta$
 ggg. The subsequent position of path-finding
 Crossarchus is engendered.
 hhh. $C_{i+1} = \begin{cases} C_i - A * O * R * [C_i - \vec{P}] \\ \text{if } \delta_{i+1} > \delta_i; [\text{Exploration}] \\ C_i + A * O * R * [C_i - \vec{P}] \\ \text{Else}; [\text{Exploitation}] \end{cases}$
 iii. Modernize best solution obtained so far
 jjj. Output the best solution
 kkk. end

Simulation Results

Hybridized Golden marmoset - Pegea confoederata -Lucihormetica verrucosa swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm are validated in 7 benchmark functions (F1- Sphere/parabola, F2- Ackley, F3- Rosen rock, F4- Generalized Griewank, F5- Hartman 3, F6- Six-hump camel-back, F7- Goldstein-Price) (Yapıcı and Çetinkaya, 2017), and results are shown in Table 1.

$$f_1 = \sum_{i=1}^D x_i^2$$

$$f_2 = -20 \exp \left\{ -0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2} \right\} - \exp \left\{ \frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i) \right\} + 20 + e$$

$$f_3 = \sum_{i=1}^{D-1} \{100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\}$$

$$f_4 = \frac{1}{4000} \sum_{i=1}^D x_i^2 - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

$$f_5 = -\sum_{i=1}^4 c_i \exp \left[-\sum_{j=1}^3 a_{ij} (x_j - p_{ij})^2 \right]$$

$$f_6 = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^3$$

$$f_7 = \{1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)\} \times \left\{ (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2) \right\}$$

Table 1. Result assessment - 7 benchmark functions

Function	H-PSO (Yapıcı and Çetinkaya, 2017)	E-PSO (Yapıcı and Çetinkaya, 2017)	HGPC	ICLV
F1	0.8874	0.0026	0.0019	0.0019
F2	0.0918	0.0125	0.0118	0.0118
F3	22.9814	16.5622	16.479	16.479
F4	1.1092 e-2	3.459 e-4	3.08 e-4	3.08 e-4
F5	-3.8629	-3.8629	-3.8578	-3.8578
F6	-1.0318	-1.0316	-1.0333	-1.0333
F7	3.0280	3.0130	3.0128	3.0128

Hybridized Golden marmoset - Pegea confoederata -Lucihormetica verrucosa swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm are validated in IEEE 57 bus system. Table 2 shows the Real Loss (RAL (MW)), Power variance (PRV (PU)), and solidity (PRT (PU)).

Table 2. Assessment of results (IEEE 57 bus)

Technique	RAL(MW)	PRV(PU)	PRT(PU)
COA (Shaheen et al., 2023)	24.5358	0.6711	0.2757
SAI (Varan et al., 2023)	26.88	1.0642	0.25297
EPSO (Lima et al., 2023)	27.83	1.10	0.30
CTO (Lenin, 2023)	23.3235	0.58553	0.2561
HGPC	20.08	0.6019	0.3284
ICLV	20.12	0.6023	0.3279

Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm are authenticated in IEEE 354 bus system. Table 3 shows the true loss valuation and Power abnormality evaluation.

Table 3. Loss and aberration appraisal (IEEE 354 bus)

Technique	RAL (MW)	PRV(PU)
SAI (Lima et al., 2023)	337.37400	0.497800
EISA (Lenin, 2023)	339.32500	0.521600
PLSO (Lenin, 2023)	341.0010	0.535400
HGPC	330.001	0.423491
ICLV	330.028	0.423501

Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm have condensed the loss efficiently in IEEE 57, 354 bus systems. Table 4 shows the time taken by HGPC and ICLV algorithms.

Table 4. Time taken by HGPC, ICLV

Method	57 bus T(S)	354 bus T(S)
HGPC	27.09	75.23
ICLV	26.98	75.19

Discussion of Results

Real power loss attained by HGPC - 20.08 (MW) and ICLV- 20.12 (MW) in the IEEE 57 bus system. In the IEEE 354 bus system, power loss is attained by HGPC - 330.001(MW) and ICLV- 330.028 (MW). Power has been reduced by the proposed HGPC and ICLV effectively.

Conclusion

Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm efficiently solved the loss lessening problem. In the Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC), regular attributes of the Golden marmoset is integrated with the Pegea confoederata swarm optimization algorithm. Copulating is a significant operative in the Golden Marmoset optimization algorithm that guarantees cluster endurance and permits the interchange of hereditary info and societal actions amongst entities. In the Pegea confoederata swarm optimization algorithm, to avoid the error in data distribution about nutrition location till the culmination of manacle, the bounce acquaintances, which are enthused from the neural networks, are integrated. In the Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm, regular activities of Crossarchus are emulated to design the algorithm, and Lucihormetica Verrucosa Swarm has been integrated into the procedure. The Crossarchus won't seizure big prey stuff, which might deliver sustenance for the entire cluster. As soon as Lucihormetica verrucosa is voracious in the interim phase, it wanders from its contented lodging and associates establishment to gaze for nutrition. Hybridized Golden marmoset - Pegea confoederata swarm optimization algorithm (HGPC) and Integrated Crossarchus -Lucihormetica Verrucosa Swarm optimization (ICLV) algorithm has been

validated in 7 benchmark functions and IEEE 57, 354 bus systems.

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