

HYBRID GUILLEMOT - CALLOSCIURUS PREVOSTII ALGORITHM

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Abstract

Hybrid Guillemot - Callosciurus prevostii Algorithm (HGC) is designed in this paper. Key objectives are active power loss reduction and voltage stability augmentation. In Guillemot algorithm, the passage of Guillemot will be in the direction of other Guillemot rendering to warmth deliberation and space. Callosciurus prevostii energetic foraging ploy and glissade process are imitated scientifically to design the algorithm. In the period of autumn season, Callosciurus prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the locations. Guillemot Algorithm and Callosciurus prevostii Optimization Algorithm are hybridized to enhance the exploration and exploitation capabilities of the algorithm in order to attain better solutions. Hybrid Guillemot - Callosciurus prevostii Algorithm (HGC) validated in IEEE 30 and 354 test systems. Active power loss reduction has been achieved with voltage deviation minimization.

Keywords: Optimization; Guillemot; Callosciurus prevostii

Introduction

Active power loss reduction and voltage stability augmentation in Power System is difficult problem. Numerous methods (Chaitanya *et al.*, 2021; Barkavi *et al.*, 2022; Zou *et al.*, 2023) are successively applied to solve the problem.

In this paper Hybrid Guillemot - Callosciurus prevostii Algorithm (HGC) applied for solving the active power loss reduction problem.

Guillemot Algorithm

In Guillemot Algorithm (GA) location and rate of Guillemot (Figure 1) (Wanless *et al.*, 2023) is calculated. Guillemot will passage in the direction of additional Guillemot which holds little rate of captivation. Rate is demarcated by the warmth

deliberation and space. Pull is accomplished, an original elucidation is appraised for that warmness deliberation is rationalized. Elucidations are prescribed consecutively and supreme is preferred. For warmth energy, drive, warmness captivation hindering proportion is smeared.

Callosciurus prevostii Optimization Algorithm

In Callosciurus prevostii Optimization Algorithm (CS) Callosciurus prevostii (Figure 2) (Lurz *et al.*, 2017) energetic foraging ploy and glissade process are imitated scientifically to design the algorithm. When Quercus rubra Callosciurus prevostii begins the foraging searching process begins. In the period of autumn season Callosciurus

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prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the location's and determine different region of the forest. CA approach starts with arbitrary preliminary location of Callosciurus prevostii in the exploration space.

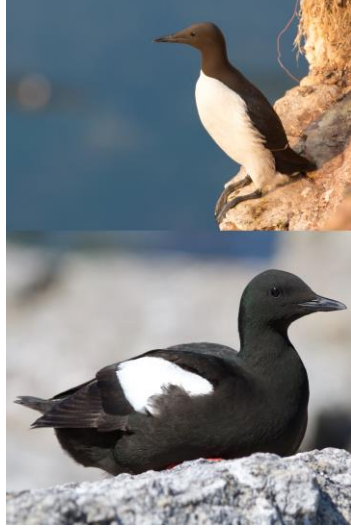


Figure 1. Guillemot image representation



Figure 2. Callosciurus prevostii image representation

Hybrid Guillemot - Callosciurus prevostii Algorithm

Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized to enhance the exploration and exploitation abilities of the algorithm. Guillemot location and rate are calculated. Guillemot will passage in the direction of additional Guillemot which holds little rate of captivation.

Rate is demarcated by the warmth deliberation and space. Pull is accomplished, an original elucidation is appraised for that warmth deliberation is rationalized. Elucidations are prescribed consecutively and supreme is preferred. Callosciurus prevostii energetic foraging ploy and glissade process are imitated scientifically to design the algorithm.

When Quercus rubra Callosciurus prevostii begins the foraging searching process begins. In the period of autumn season Callosciurus prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the location's and determine different region of the forest. Key attributes of Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized.

Problem Formulation

True power loss reduction and voltage stability enhancement is delineated as,

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

$$M(\bar{g}, \bar{h}) = 0 \quad (2)$$

$$N(\bar{g}, \bar{h}) = 0 \quad (3)$$

Then the control ($\bar{g}$) and dependent ($\bar{h}$) vectors are defined as,

$$g = [VLG_1, \dots, VLG_{Ng}; QC_1, \dots, QC_{Nc}; T_1, \dots, T_{Nr}] \quad (4)$$

$$h = [PG_{slack}; VL_1, \dots, VL_{Nload}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{Nr}] \quad (5)$$

$$F_1 = P_{Min} = \text{Min} \left[\sum_{m=1}^{NTL} G_m [V_i^2 + V_j^2 - 2 * V_i V_j \cos \theta_{ij}] \right] \quad (6)$$

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

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

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

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

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

Parity constraints

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

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

Disparity constraints

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

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

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

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

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

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

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

$$\text{Multi objective fitness (MOF)} = F_1 + r_1 F_2 + u F_3 = F_1 + \left[\sum_{i=1}^{NL} x_v [VL_i - VL_i^{\min}]^2 + \sum_{i=1}^{NG} r_g [QG_i - QG_i^{\min}]^2 \right] + r_f F_3 \quad (21)$$

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

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

Hybrid Guillemot - Callosciurus prevostii Optimization Algorithm

Key attributes of Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized. Through the Guillemot Algorithm, Callosciurus prevostii Optimization Algorithm hybridization (HGC) exploration and exploitation abilities of the algorithm are enhanced.

Guillemot Algorithm

In this proposed approach nature deeds of Guillemot are imitated to model the Guillemot Algorithm (GA). Guillemot location and rate are calculated. Guillemot will passage in the direction of additional Guillemot which holds little rate of captivation. Rate is demarcated by the warmth deliberation and space. Pull is accomplished, an original elucidation is appraised for that warmness deliberation is rationalized. Elucidations are prescribed consecutively and supreme is preferred.

For warmth energy, drive, warmness captivation hindering proportion is smeared.

Superficial part of the physique of Guillemot is defined as,

$$R_s = 2\pi \frac{ab}{e} \sin^{-1} e + 2\pi b^2 \quad (24)$$

Computation of Break area is done through,

$$R_b = \pi r s \quad (25)$$

Crown area of Guillemot is premeditated by,

$$R_h = \pi d^2 - \pi r^2 \quad (26)$$

Design of paddle is completed by,

$$R_p = l \times w \quad (27)$$

Contingent on the atmosphere,

$$a_{sum} = a_s + a_h + a_p + q_f \quad (28)$$

As of each physique of Guillemot warmness energy released in that specific external zone is premeditated as,

$$U_s = \text{Space} \cdot \varepsilon \cdot \sigma \cdot W_s^4 \quad (29)$$

Reception the warmness in the external zone is premeditated as,

$$WE = W_o \quad (30)$$

The concentration of the warmness is,

$$We = WE_o / \text{Space}^2 \quad (31)$$

Rendering to initial rate V_o once the warmth spring is rectilinear,

$$V = v_o / \text{space} \quad (32)$$

Diminution factor is

$$WE = WE_o e^{-\mu m} \quad (33)$$

The attractiveness is defined by,

$$U = \text{Space} \cdot \varepsilon \cdot \sigma \cdot W_s^4 \cdot e^{-\mu m} \quad (34)$$

Helix drive of Guillemot is,

$$\text{space} = g e^{h\theta} \quad (35)$$

$$m = s \cos \theta = g \cos \theta e^{h\theta} \quad (36)$$

$$n = s \sin \theta = g \sin \theta e^{h\theta} \quad (37)$$

Expanse between two Guillemot “i” and “j” is calculated,

$$R_{ij} = \int_i^j ds = \int_{\theta_i}^{\theta_j} \sqrt{\left(\frac{ds}{d\theta}\right)^2 + R^2} d\theta = \int_{\theta_i}^{\theta_j} \sqrt{g^2 h^2 e^{2h\theta} + g^2 e^{2h\theta}} d\theta = g \sqrt{h^2 + 1} \int_{\theta_i}^{\theta_j} e^{h\theta} d\theta = \frac{g}{h} \sqrt{h^2 + 1} (e^{h\theta_j} - e^{h\theta_i}) \quad (38)$$

Space is premeditated as,

$$R_{ik} = U \frac{g}{h} \sqrt{h^2 + 1} (e^{h\theta_j} - e^{h\theta_i}) = \int_i^k ds = \frac{g}{h} \sqrt{h^2 + 1} (e^{h\theta_k} - e^{h\theta_i}) \quad (39)$$

$$\theta = \tan^{-1} \frac{n}{m} \quad (40)$$

$$m_k = g \cos \theta_k e^{h\theta_k} \quad (41)$$

$$n_k = g \sin \theta_k e^{h\theta_k} \quad (42)$$

Constituents of the location is attained by,

$$m_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \cos \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \quad (43)$$

$$n_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \sin \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \quad (44)$$

Helix drive of Guillemot i added and stimulated to fresh location as,

$$m_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \cos \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} + \Delta \sigma_i \quad (45)$$

$$n_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \sin \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} + \Delta \sigma_i \quad (46)$$

- a. Start
- b. Create initial population
- c. Stimulate the location of Guillemot
- d. Find the rate of every Guillemot
- e. Discover the primary warmth captivation quantity
- f. *For* $t = 1$ *to* $Max.iter$ *do*
- g. Stimulate the imitate of populace range
- h. *For* $i = 1$ *to* n *P do*
- i. *For* $j = 1$ *to* n *P do*
- j. *if* $rate\ j < rate\ i$; *then*
- k. Calculate the warmth energy rate
- l. $U_s = Space \cdot \varepsilon \cdot \sigma \cdot W_s^4$
- m. Calculate the pull rate
- n. $U = Space \cdot \varepsilon \cdot \sigma \cdot W_s^4 \cdot e^{-\mu m}$
- o. Calculate the harmonized helix drive
- p. $m_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\}$
- q. $n_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\}$
- r. Discover the fresh location
- s. $m_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \cos \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} + \Delta \sigma_i$
- t. $n_k = ge \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} \sin \left\{ \frac{1}{h} \ln \left\{ (1-U)e^{h \tan^{-1} \frac{n_i}{m_i}} + Ue^{h \tan^{-1} \frac{n_j}{m_j}} \right\} \right\} + \Delta \sigma_i$
- u. Assessment of fresh elucidations
- v. End
- w. Organize and determine premium elucidation
- x. Streamline the warmth energy rate
- y. Revolutionise the alteration coefficient
- z. Update the warmth captivation coefficient
- aa. Output the solution
- bb. End

Callosciurus prevostii Optimization Algorithm

Callosciurus prevostii energetic foraging ploy and glissade process are imitated scientifically to design the algorithm. When Quercus rubra Callosciurus prevostii begins the foraging searching process begins. In the period of autumn season Callosciurus prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the location's and determine different region of the forest. Callosciurus prevostii Optimization Algorithm (CA) starts with arbitrary preliminary location of Callosciurus prevostii and location of Callosciurus prevostii is characterized by a vector, in "d" dimensional exploration space. In forest there will be "n" number of Callosciurus prevostii and location of i_{th} Callosciurus prevostii can be determined by a vector. Callosciurus prevostii location is designated by,

$$FY = \begin{bmatrix} FY_{1,1} & \cdots & FY_{1,d} \\ \vdots & \ddots & \vdots \\ FY_{n,1} & \cdots & FY_{n,d} \end{bmatrix} \quad (47)$$

In the woods preliminary position of each Callosciurus prevostii is described by,

$$FY_i = FY_L + U(0,1) \times (FY_U - FY_L) \quad (48)$$

Callosciurus prevostii locality fitness value is calculated by,

$$fitness(f) = \begin{bmatrix} |f_1(|FY_{1,1}, FY_{1,2}, \dots, FY_{1,d}|)| \\ |f_2(|FY_{2,1}, FY_{2,2}, \dots, FY_{2,d}|)| \\ \vdots \\ |f_n(|FY_{n,1}, FY_{n,2}, \dots, FY_{n,d}|)| \end{bmatrix} \quad (49)$$

Callosciurus prevostii will move from the Quercus rubras (FY_{α}) and novel locality of Callosciurus prevostii can be obtained by,

$$FY_{at}^{t+1} = \begin{cases} FY_{at}^{t+1} = FY_{at}^t + d_g \times G_c \times (FY_{ht}^t - FY_{at}^t) & A_1 \geq Z_{dp} \\ \text{arbitrary place} & \text{or else} \end{cases} \quad (50)$$

From normal Quercus rubras (FY_{nt}) Callosciurus prevostii will move to next Quercus rubra for achieving the requirements. Then the novel locality of Callosciurus prevostii is given by,

$$FY_{nt}^{t+1} = \begin{cases} FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{at}^t - FY_{nt}^t) & A_2 \geq Z_{dp} \\ \text{arbitrary place} & \text{or else} \end{cases} \quad (51)$$

In order to accumulate nuts Callosciurus prevostii will advance towards Quercus rubras and novel location is given by,

$$FY_{nt}^{t+1} = \begin{cases} FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{ht}^t - FY_{nt}^t) & A_3 \geq Z_{dp} \\ \text{arbitrary place} & \text{or else} \end{cases} \quad (52)$$

Callosciurus prevostii glissade is described as,

$$FYG = 1/2\rho V^2 SFY_{cg} \quad (53)$$

Glissade angle is determined by,

$$\Phi = \arctan\left(\frac{FYG}{L}\right) \quad (54)$$

Glissade distance (cgd) roughly determined by,

$$cgd = \left(\frac{cg}{\tan\Phi}\right) \quad (55)$$

Quercus rubra Callosciurus prevostii affected by the time variation and it described by

$$FY_c^t = \sqrt{\sum_{k=1}^d (FY_{at,k}^t - FY_{ht,k}^t)^2} \quad (56)$$

Investigate the time examination condition by; $T_c^t < T_{min}$ and the value of T_{min} is determined by,

$$T_{min} = \frac{10E^{-6}}{(365)^t / (t_m / 2.5)} \quad (57)$$

Relocation of Quercus rubra Callosciurus prevostii defined by,

$$FY_{nt}^{new} = FY_L + Levy(n) \times (FY_U - FY_L) \quad (58)$$

Levy flight incorporated as,

$$L(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} & \exp\left[-\frac{\gamma}{2(s-\mu)}\right] \\ 0 & \text{if } s \leq 0 \end{cases} \quad (59)$$

$$\frac{1}{(s-\mu)^{3/2}} \quad \text{if } 0 < \mu < s < \infty$$

$$F(k) = \exp[-\alpha|k|^\beta], 0 < \beta \leq 2,$$

$$FY^{t+1} = FY^t + \alpha \oplus Levy(\beta)$$

$$FY^{t+1} = FY^t + \text{arbitrary}(\text{size}(FYG)) \oplus Levy(\beta)$$

$$FY^{t+1} = FY^t + \text{arbitrary}(\text{size}(FYG)) \oplus$$

$$Levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} (x_j^t - gb)$$

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2)$$

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

- a. Start
- b. Variables are fixed
- c. Kindle changeable position for n number of Quercus rubra Callosciurus prevostii
- d. $FY_i = FY_L + U(0,1) \times (FY_U - FY_L)$
- e. For every Quercus rubra Callosciurus prevostii position verify the fitness value
- f. In ascending command - set up the position of Quercus rubra Callosciurus prevostii
- g. Set up the Quercus rubra Callosciurus prevostii
- h. Variably decide a number of Quercus rubra Callosciurus prevostii
- i. While (stop condition is not satisfied)
- j. For t = 1 to n1 (n1 = sum of Quercus rubra Callosciurus prevostii which are on the acorn Quercus rubras and moving in the direction of Quercus rubras)
- k. *if* $A_1 \geq Z_{dp}$
- l. $FY_{at}^{t+1} = FY_{at}^t + d_g \times G_c \times (FY_{ht}^t - FY_{at}^t)$
- m. Else
- n. $FY_{at}^{t+1} =$
an arbitrary place in exploration space
- o. End
- p. For t = 1 to n2 (n2 = sum of Quercus rubra Callosciurus prevostii in normal Quercus rubras and moving towards acorn Quercus rubras)
- q. *if* $A_2 \geq Z_{dp}$
- r. $FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{at}^t - FY_{nt}^t)$
- s. Else
- t. $FY_{nt}^{t+1} =$
an arbitrary place in exploration space
- u. End
- v. For t = 1 to n3 (n3 = sum of Quercus rubra Callosciurus prevostii in normal Quercus rubras and moving towards Quercus rubras)
- w. *if* $A_3 \geq Z_{dp}$
- x. $FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{ht}^t - FY_{nt}^t)$
- y. Else
- z. $FY_{nt}^{t+1} =$
an arbitrary place in exploration space
- aa. End
- bb. Compute the moment of occasion
- cc. If (scrutinize condition is satisfied)
- dd. Variably reposition Quercus rubra Callosciurus prevostii

- ee. $FY_{nt}^{new} = FY_L + Levy(n) \times (FY_U - FY_L)$
- ff. End
- gg. Modify the least value of time
- hh. End
- ii. Out put the most excellent solution
- jj. End

Hybrid Guillemot -Callosciurus prevostii Algorithm

Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized to enhance the exploration and exploitation abilities of the algorithm. Guillemot location and rate are calculated. Guillemot will passage in the direction of additional Guillemot which holds little rate of captivation. Rate is demarcated by the warmth deliberation and space. Pull is accomplished, an original elucidation is appraised for that warmth deliberation is rationalized. Elucidations are prescribed consecutively and supreme is preferred. Callosciurus prevostii energetic foraging ploy and glissade process are imitated scientifically to design the algorithm. When Quercus rubra Callosciurus prevostii begins the foraging searching process begins. In the period of autumn season Callosciurus prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the location's and determine different region of the forest. Key attributes of Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized.

- a. Start
- b. Initialize the parameters
- c. Engender the population
- d. // Guillemot algorithm//
- e. Stimulate the location of Guillemot
- f. Find the rate of every Guillemot
- g. Discover the primary warmth captivation quantity
- h. *For* t = 1 *to* Max.iter *do*
- i. Stimulate the imitate of populace range
- j. *For* i = 1 *to* n P *do*
- k. *For* j = 1 *to* n P *do*
- l. *if* rate j < rate i ; *then*
- m. Calculate the warmth energy rate
- n. $U_s = Space \cdot \varepsilon \cdot \sigma \cdot W_s^4$
- o. Calculate the pull rate
- p. $U = Space \cdot \varepsilon \cdot \sigma \cdot W_s^4 \cdot e^{-\mu m}$
- q. Calculate the harmonized helix drive
- r. Discover the fresh location
- s. Assessment of fresh elucidations
- t. End

- u. Organize and determine premium elucidation
- v. Streamline the warmth energy rate
- w. Revolutionise the alteration coefficient
- x. Update the warmness captivation coefficient
- y. End while
- z. // Callosciurus prevostii algorithm//
- aa. Kindle changeable position for n number of Quercus rubra Callosciurus prevostii
- bb. $FY_i = FY_L + U(0,1) \times (FY_U - FY_L)$
- cc. For every Quercus rubra Callosciurus prevostii position verify the fitness value
- dd. In ascending command - set up the position of Quercus rubra Callosciurus prevostii
- ee. Set up the Quercus rubra Callosciurus prevostii
- ff. Variably decide a number of Quercus rubra Callosciurus prevostii
- gg. While (stop condition is not satisfied)
- hh. For t = 1 to n1 (n1 = sum of Quercus rubra Callosciurus prevostii which are on the acorn Quercus rubras and moving in the direction of Quercus rubras)
- ii. $FY_{at}^{t+1} = FY_{at}^t + d_g \times G_c \times (FY_{ht}^t - FY_{at}^t)$
- jj. Else
- kk. $FY_{at}^{t+1} =$
an arbitrary place in exploration space
- ll. End
- mm. For t = 1 to n2 (n2 = sum of Quercus rubra Callosciurus prevostii in normal Quercus rubras and moving towards acorn Quercus rubras)
- nn. if $A_2 \geq Z_{dp}$
- oo. $FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{at}^t - FY_{nt}^t)$
- pp. Else
- qq. $FY_{nt}^{t+1} =$
an arbitrary place in exploration space
- rr. End
- ss. For t = 1 to n3 (n3 = sum of Quercus rubra Callosciurus prevostii in normal Quercus rubras and moving towards Quercus rubras)
- tt. if $A_3 \geq Z_{dp}$
- uu. $FY_{nt}^{t+1} = FY_{nt}^t + d_g \times G_c \times (FY_{ht}^t - FY_{nt}^t)$
- vv. Else
- ww. $FY_{nt}^{t+1} =$
an arbitrary place in exploration space
- xx. Compute the moment of occasion
- yy. If (scrutinize condition is satisfied)
- zz. Variably reposition Quercus rubra Callosciurus prevostii

- aaa. Modify the least value of time
- bbb. Output the optimal solution
- ccc. End

Results and discussion section

Hybrid Guillemot -Callosciurus prevostii Algorithm (HGC) validated in IEEE 30 bus system. Table 1 shows the active power loss (A (MW)), voltage deviation (D (PU)) and Stability (S (PU)). Figures 3-5 give the valuation of results.

Table 1. Appraisal of resuts (ieec 30 bus)

Method	A(MW)	D(PU)	S(PU)
PD (Ali MH <i>et al.</i> , 2023)	4.8395	1.2663	0.1259
RS (Ali MH <i>et al.</i> , 2023)	5.1328	1.0240	0.1287
AV (Ali MH <i>et al.</i> , 2023)	4.5464	1.9889	0.1294
RO (Ali MH <i>et al.</i> , 2023)	4.6271	1.5865	0.1289
SP (Ali MH <i>et al.</i> , 2023)	4.5730	1.8257	0.1262
DE (Pg <i>et al.</i> , 2022)	4.6482	0.0802	0.1394
WO (Abd-El Wahab <i>et al.</i> , 2022)	4.9448	0.1212	0.1402
PA (Habib Khan <i>et al.</i> , 2022)	4.5677	0.1250	0.1414
GA	4.4912	0.0821	0.1487
CA	4.4915	0.0826	0.1485
HGC	4.4908	0.0810	0.1498

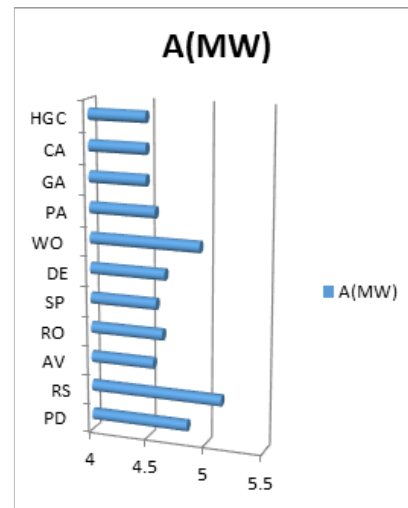


Figure 3. Assessment of A(MW) (IEEE 30 bus)

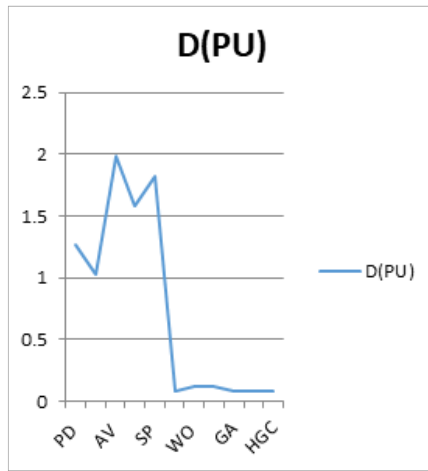


Figure 4. Assessment of D(PU) (IEEE 30 bus)



Figure 5. Assessment of S(PU) (IEEE 30 bus)

Projected Guillemot -Callosciurus prevostii Algorithm performed well in active power loss reduction, Voltage deviation minimization and Voltage stability enhancement. The values obtained by HGC algorithm in IEEE 30 bus system are Active power loss- 4.4908 (MW), Voltage deviation minimization - 0.0810 (PU) and Voltage stability enhancement - 0.1498 (PU). Projected HGC algorithm has been compared with other standard reported algorithms, which shown in Table 1 and Figures 3-5.

Table 2. Valuation of result (ieee 354)

Method	A(MW)	D(PU)
SAI (Mouassa and Bouktir, 2019)	337.374	0.4978
SAII (Mouassa and Bouktir, 2019)	338.715	0.5117
SA (Mouassa and Bouktir, 2019)	339.325	0.5216
SO (Nagarajan <i>et al.</i> , 2020)	341.001	0.5354
PSO (Nagarajan <i>et al.</i> , 2020)	341.123	0.6395
PO (Kanagasabai, 2023)	336.025	0.4821
CJSO (Kanagasabai, 2023)	336.017	0.4819
QCS (Kanagasabai, 2023)	336.011	0.4813
GA	332.786	0.4578
CA	332.989	0.4575
HGC	331.675	0.4596

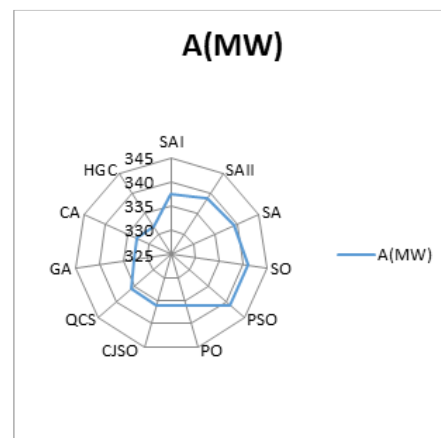


Figure 6. Valuation of A(MW) (IEEE 354 bus)

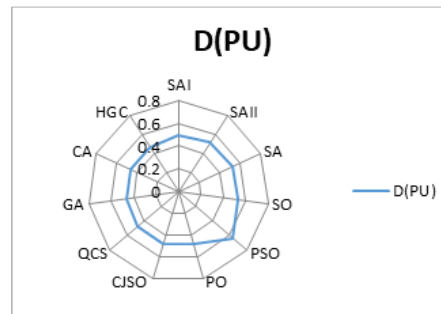


Figure 7. Valuation of D(PU) (IEEE 354 bus)

Hybrid Guillemot - Callosciurus prevostii Algorithm (HGC) validated in IEEE 354 bus system. Table 2, Figure 6 and Figure 7 shows the valuation. (Active power loss (A (MW)), voltage deviation (D (PU)))

Hybridized Guillemot -Callosciurus prevostii Algorithm (HGC) solved the problem competently. Active power loss reduction, minimization of voltage deviation and stability development has been reached.

Projected Guillemot -Callosciurus prevostii Algorithm performed well in active power loss reduction and Voltage deviation minimization. The values obtained by HGC algorithm in IEEE 354 bus system are Active power loss- 331.675 (MW) and Voltage deviation minimization - 0.4596 (PU). Projected HGC algorithm has been compared with other standard reported algorithms, which shown in Table 2, Figure 6 and Figure 7.

Table 3 and Figure 8 show the time taken by Hybridized Guillemot -Callosciurus prevostii Algorithm (HGC).

Table 3. Time taken by GA, CA, HGC

Method	30 BUS T(S)	354 T(S)
GA	17.14	84.13
CA	16.99	83.98
HGC	15.87	81.78

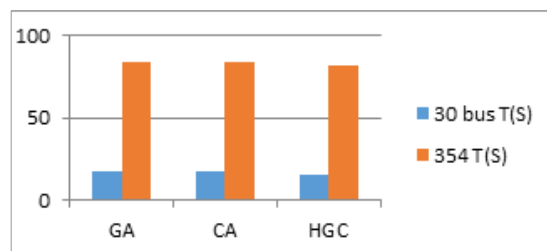


Figure 8. Time taken by GA, CA, HGC

Conclusions

Hybrid Guillemot - Callosciurus prevostii Algorithm (HGC) solved the problem competently. Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized to enhance the exploration and exploitation abilities of the algorithm.

In Guillemot algorithm, the passage of Guillemot will be in the direction of other Guillemot rendering to warmth deliberation and space. Callosciurus prevostii energetic foraging ploy and glissade process are imitated scientifically to design the algorithm.

In the period of autumn season, Callosciurus prevostii seek for food resources by glissade from one Quercus rubra to another, and they change the locations.

Key attributes of Guillemot Algorithm (GA) and Callosciurus prevostii Optimization Algorithm (CA) are hybridized.

Hybrid Guillemot -Callosciurus prevostii Algorithm (HGC) validated in IEEE 30 and 354 test systems.

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