

NOVEL HYBRID ASIATIC CHEETAH - GOBI BEAR OPTIMIZATION AND INTEGRATED HAMERKOP - ZEUGODACUS FULVOABDOMINALIS ALGORITHM FOR POWER LOSS DIMINUTION AND VOLTAGE STABILITY ENLARGEMENT

Lenin Kanagasabai*

Received: March 24, 2025; Revised: July 21, 2025; Accepted: July 21, 2025

Abstract

The Asiatic cheetah optimization algorithm is grounded on the besieged stalking approach of the Asiatic cheetah, which comprises an order of activities: probing for prey, patiently waiting for the accurate instant to attack, rapidly initiating the attack, receding from the prey, and coming back to the habitat. Numerous intellectual activities of the Gobi bear, such as tracking the cluster, detecting food sources, and navigating the terrain, are considered in the design. Gobi bear utilizes lever odour marking and snuffling activities in the habitat. In the unique method of passaging by Gobi bears, there will be repeated odour marking, confirming earlier marked prints. The Asiatic cheetah optimization algorithm is hybridized with the Gobi bear optimization algorithm. Hamerkop enactment and approach in the course of pestering is an intelligent method, and this habit has been imitated to model the procedure. In Zeugodacus fulvoabdominalis, owing to their very tremendous sightedness and conjoint compassionate deeds Zeugodacus fulvoabdominalis will discover the sustenance deprived of exertion. Hamerkop optimization algorithm integrated with Zeugodacus fulvoabdominalis optimization algorithm. The Hybrid Asiatic Cheetah - Gobi Bear Optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis Optimization (IHZFO) algorithm are substantiated using seven benchmark functions and the IEEE 30 and 57 bus systems.

Keywords: Asiatic cheetah; Gobi bear; Prey; Hamerkop; Zeugodacus fulvoabdominalis

Introduction

Hybrid Asiatic cheetah - Gobi bear optimization (HACGB) algorithm and Integrated Hamerkop - Zeugodacus fulvoabdominalis optimization (IHZFO) algorithm are defined to solve the loss lessening APE (Ali *et al.*, 2023); GWM (Varan *et al.*, 2023); AQM (Lian, 2022); PQS1 (Sahli, *et al.*, 2022); PQO (Hasanien *et al.*, 2024); GTS (Gil *et al.*, 2024); MOP (In *et al.*, 2024); ETS (Shaheen *et al.*, 2023); LPA (Khan *et al.*, 2024); PAU (Rao *et al.*, 2024); SARANI (kanagasabai, 2024); Analytical method (Pushkarna *et al.*, 2022); Heuristic approach (Kumar *et al.*, 2024); Hybrid

Prasad V. Potluri Siddhartha Institute of Technology Chalasani Nagar, Kanuru, Vijayawada, Andhra Pradesh, 520007, India
E-mail: gklenin@gmail.com

* Corresponding author

DOI: <https://doi.org/10.55766/sujst9167>

Suranaree J. Sci. Technol. 32(6):010392(1-10)

technique (Kumar *et al.*, 2022) PSO (Pushkarna *et al.*, 2024) and PSO-BFOA (Kumar *et al.*, 2021) problem. The Asiatic cheetah optimization algorithm is grounded on the besieged stalking approach engaged by the Asiatic cheetah (Safiyan-Boldaji *et al.*, 2024), which comprises an order of activities: probing for prey, tolerantly waiting for the accurate instant to attack, rapidly initiating the attack, receding from the prey, and coming back to the habitat. The Gobi bear optimization algorithm is grounded in the searching performance of the Gobi bear (Anile *et al.*, 2024). Numerous intellectual activities of the Gobi bear, such as tracking the cluster, detecting food sources, and navigating the terrain, are considered in the design. Gobi bear utilizes lever odour marking and snuffling activities in the habitat. The Asiatic cheetah optimization algorithm is hybridized with the Gobi bear optimization algorithm. During the period of probing for prey, each Asiatic cheetah selects different prey positions, indicating the primary decision parameters that influence the population's conditions. The arbitrary examination modernizes the new location of the Asiatic cheetah, each plan based on the current location and random step magnitude. Asiatic cheetahs attack their prey with high swiftness and elasticity. In the Gobi bear optimization algorithm initialization phase, arbitrary solution sets are created, which signify the cluster of Gobi bears representing groups of brown bears, and odor is considered a decision variable within the habitat. The Gobi bear employs a unique method of passing, where it kinks its feet to evade the aforementioned marks on the ground and prudently steps in the direction of the besieged area. Gobi bears engage in snuffling to track the lever odour markings of the cluster members in the accurate direction. Furthermore, Gobi bears utilize snuffling to create their terrain and evade being deceived by the lever odour markings of other clusters. Hamerkop enactment and approach in the course of pestering is an intelligent method, and this habit has been imitated to model the procedure. Hamerkop (Hagemeyer, 2016) are acquaintances of the inhabitants, and each population companion endorses a degree for the optimal problem constraints interpreting to their position in the examination area. Primarily, inhabitants' companions are capriciously geared up interpreting to the lowest and extreme restrictions of the problem. Hamerkop optimization algorithm plays the enactment and scheme of hamerkop whereas antagonizing and pestering the quarry to assess candidate explications. This pestering scheme is completed through Rousing in the course of quarry, which serves as an exploration section, and the

waterside is engaged as an exploitation section. In the exploration section, Hamerkop identifies the spot of the quarry and then passes through the course of the recognized region. In Zeugodacus fulvoabdominalis (Meyer *et al.*, 2016), owing to their very tremendous sightedness and conjoint compassionate deeds Zeugodacus fulvoabdominalis will discover the sustenance deprived of exertion. Each Zeugodacus fulvoabdominalis upholds a track from its position, and the passage will be in the course of sustenance. A divergent class of Pong is matched, and a prime sustenance zone will be designated. At that moment, main attentiveness is designated as the optimal present position. The Hybrid Asiatic Cheetah - Gobi Bear Optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis Optimization (IHZFO) algorithm are substantiated using seven benchmark functions and the IEEE 30 and 57 bus systems.

Problem Formulation

Power loss diminution is technically termed as,

$$\text{Min } \tilde{F}(\bar{a}, \bar{b}) \quad (1)$$

$$\begin{aligned} a &= \begin{bmatrix} VLG_1, \dots, VLG_{Ng}; QC_1, \dots, QC_{Nc} \\ T_1, \dots, T_{N_T} \end{bmatrix} \\ b &= \begin{bmatrix} PG_{slack}; VL_1, \dots, VL_{N_{load}}; QG_1, \dots, QG_{Ng} \\ SL_1, \dots, SL_{N_T} \end{bmatrix} \\ F_1 &= P_{Min} = \text{Min} \left[\sum_m^{NTL} G_m [V_i^2 + V_j^2 - 2 * V_i V_j \cos \theta_{ij}] \right] \\ F_2 &= \text{Min} \left[\sum_{l=1}^{NLB} |V_{Lk} - V_{Lk}^{desired}|^2 + \sum_{i=1}^{Ng} |Q_{GK} - Q_{KG}^{Lim}|^2 \right] \\ F_3 &= \text{Minimize } L_{Maximum} \\ &\begin{cases} L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j} \\ F_{ji} = -[Y_1]^1 [Y_2] \end{cases} \end{aligned}$$

Equality constraints

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \cos[\theta_i - \theta_j] + B_{ij} \sin[\theta_i - \theta_j]] \quad (2)$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \sin[\theta_i - \theta_j] + B_{ij} \cos[\theta_i - \theta_j]] \quad (3)$$

Inequality constraints

$$P_{gsl}^{\min} \leq P_{gsl} \leq P_{gsl}^{\max} \quad (4)$$

Reactive power generation (QGi)

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (5)$$

Load bus voltage (VLi)

$$VL_i^{\min} \leq VL_i \leq VL_i^{\max}, i \in NL \quad (6)$$

Transformers tap setting (Ti)

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (7)$$

Switchable reactive power compensations (QCi)

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_C \quad (8)$$

$$|SL_i| \leq S_{Li}^{\max}, i \in N_{TL} \quad (9)$$

Generator bus voltage (VGi)

$$VG_i^{\min} \leq VG_i \leq VG_i^{\max}, i \in N_g \quad (10)$$

$$F = F_1 + r_1 F_2 + u F_3 = F_1 + \left[\sum_{i=1}^{NL} x_v [VL_i - VL_i^{\min}]^2 + \sum_{i=1}^{NG} r_g [QG_i - QG_i^{\min}]^2 \right] + r_f F_3 \quad (11)$$

$$VL_i^{\min} = \begin{cases} VL_i^{\max}, & VL_i > VL_i^{\max} \\ VL_i^{\min}, & VL_i < VL_i^{\min} \end{cases}$$

$$QG_i^{\min} = \begin{cases} QG_i^{\max}, & QG_i > QG_i^{\max} \\ QG_i^{\min}, & QG_i < QG_i^{\min} \end{cases}$$

Hybrid asiatic cheetah - gobi bear optimization algorithm

The Asiatic cheetah optimization algorithm is based on the stalking approach of the Asiatic cheetah, which involves a sequence of activities: probing for prey, patiently waiting for the optimal moment to attack, rapidly initiating the attack, retreating from the prey, and returning to the habitat. The Gobi bear optimization algorithm is grounded on the searching performance of the Gobi bear. Numerous intellectual activities of the Gobi bear, such as tracking the cluster, detecting food sources, and navigating the terrain, are considered in the design. Gobi bear utilizes lever odour marking and snuffling activities in the habitat. The Asiatic cheetah optimization algorithm is hybridized with the Gobi bear optimization algorithm. Through this integration, the algorithm's exploitation potency is enhanced. The Asiatic cheetah probes its environs to discover prey. Asiatic cheetah waits for superior chances after identifying the prey—Asiatic cheetah attacks quickly, then seizes the prey with swiftness and elasticity. Move to the habitat after receding

from the prey: Asiatic cheetahs alter their location if ineffective or reoccur to the preceding prey's position if no effective stalking occurs within a specified time interval.

During the period of probing for prey, each Asiatic cheetah pursues different prey positions, indicating the key decision parameters that influence the population's conditions. The arbitrary examination modernizes the new location of the Asiatic cheetah, each plan based on the current location and random step magnitude.

$$Y_{i,j}^{t+1} = Y_{i,j}^t + N_{i,j}^{-1} + \beta_{i,j}^t \quad (12)$$

$Y_{i,j}^t \rightarrow$ present location

$Y_{i,j}^{t+1} \rightarrow$ updated location

$N \rightarrow$ standard normal distribution

$\beta_{i,j}^t \rightarrow$ random parameter

The Asiatic cheetah patiently awaits the prey, and it is defined as,

$$Y_{i,j}^{t+1} = Y_{i,j}^t \quad (13)$$

Asiatic cheetahs attack their prey with high swiftness and elasticity. Consequently, the Asiatic cheetahs utilize maximum quickness while tracking the prey. An Asiatic cheetah diligently chases the prey, regulating its passage to wedge the prey's track, and this action causes the prey to alter its position in a random mode. While Asiatic cheetah hunts in cluster mode then leader Asiatic cheetah will guide the cluster during the preying activities.

$$Y_{i,j}^{t+1} = Y_{i,j}^t + N_{i,j} \cdot \gamma_{i,j}^t \quad (14)$$

$Y_{i,j}^t \rightarrow$ present location

In the Gobi bear optimization algorithm initialization phase, arbitrary solution sets are created, which signify the cluster of Gobi bears representing groups of brown bears, and odor is considered a decision variable within the habitat. An arbitrarily designated cluster of Gobi bears inside the pre-defined habitat is mathematically expressed as,

$$X_{i,j} = X_{i,j}^{\min} + A(X_{i,j}^{\max} - X_{i,j}^{\min}) \quad (15)$$

$$A = [0,1]$$

Gobi bear engages a unique method of passing, where they kink their feet to evade aforementioned marks on the place and prudently step in the direction of the besieged place. This particular passing performance is generally

witnessed in male Gobi bears, and this activity is mathematically expressed as,

$$X_{i,j,k}^n = X_{i,j,k}^p - (\theta_k \beta_{i,j,k} X_{i,j,k}^p) \quad (16)$$

$n \rightarrow new$

$p \rightarrow previous$

$X_{i,j,k}^n \rightarrow$ modernized odour marking

$\theta_k \in [0,1]$

$\beta_{i,j,k} \in [0,1]$

In the unique method of passing by Gobi bears, there will be repeated odour marking by confirming earlier marked prints. This performance will help alert other members in the cluster effectively.

$$X_{i,j,k}^n = X_{i,j,k}^p + S_k(X_{j,k}^b - Q_k X_{j,k}^w) \quad (17)$$

$b \rightarrow best$

$w \rightarrow worst$

$S_k \rightarrow step\ parameter$

$Q_k \rightarrow step\ length$

Gobi bear kink the feet during the passing, and this action is defined as,

$$X_{i,j,k}^n = X_{i,j,k}^p + \varphi_{i,k}(X_{j,k}^b - X_{j,k}^p) - (X_{j,k}^w - X_{j,k}^p) \quad (18)$$

$b \rightarrow best$

$w \rightarrow worst$

$p \rightarrow previous$

$\varphi_{i,k} \rightarrow$ lever odour marking

Gobi bears, engages snuffling to track the lever odour markings of the cluster members in the accurate direction. Furthermore, Gobi bears utilize snuffling to create their terrain and evade being deceived by the lever odour markings of other clusters.

$$X_{h,j,k}^n = \begin{cases} X_{h,j,k}^p + \varphi_{j,k}(X_{h,j,k}^p - X_{g,j,k}^p) \\ \quad \text{if } f(X_{h,k}^p) < f(X_{g,k}^p) \\ X_{h,j,k}^p + \varphi_{j,k}(X_{g,j,k}^p - X_{h,j,k}^p) \\ \quad \text{if } f(X_{g,k}^p) < f(X_{h,k}^p) \end{cases} \quad (19)$$

$\theta_{j,k} \in [0,1], g \neq h$

$X_{h,j,k}^n \rightarrow$ modernized odour marking

1. Begin
2. Set the values
3. Population is produced randomly
4. $Y_{i,j}^{t+1} = Y_{i,j}^t + N_{i,j}^{-1} + \beta_{i,j}^t$
5. Define the waiting period

6. Define the preying activity

$$7. Y_{i,j}^{t+1} = Y_{i,j}^t + N_{i,j} \cdot \gamma_{i,j}^t$$

$$8. X_{i,j} = X_{i,j}^{min} + A(X_{i,j}^{max} - X_{i,j}^{min})$$

9. Describe the cluster

$$10. X_{i,j,k}^n = X_{i,j,k}^p - (\theta_k \beta_{i,j,k} X_{i,j,k}^p)$$

$$11. X_{i,j,k}^n = X_{i,j,k}^p + S_k(X_{j,k}^b - Q_k X_{j,k}^w)$$

12. Outline the passing activity

$$13. X_{i,j,k}^n = X_{i,j,k}^p + \varphi_{i,k}(X_{j,k}^b - X_{j,k}^p) - (X_{j,k}^w - X_{j,k}^p)$$

14. Compute the odour marking activity

$$15. X_{h,j,k}^n = \begin{cases} X_{h,j,k}^p + \varphi_{j,k}(X_{h,j,k}^p - X_{g,j,k}^p) \\ \quad \text{if } f(X_{h,k}^p) < f(X_{g,k}^p) \\ X_{h,j,k}^p + \varphi_{j,k}(X_{g,j,k}^p - X_{h,j,k}^p) \\ \quad \text{if } f(X_{g,k}^p) < f(X_{h,k}^p) \end{cases}$$

16. Define the snuffling activity

$$17. t = t + 1$$

18. End

Integrated hamerkop - zeugodacus fulvoabdominalis algorithm

Hamerkop enactment and approach in the course of pestering is an intelligent method, and this habit has been imitated to model the procedure. Hamerkop is an acquaintance of the inhabitants, and each population companion endorses a degree for the optimal problem constraints interpreting to their position in the examination area. Primarily, inhabitants' companions are capriciously geared up interpreting to the lowest and extreme restrictions of the problem.

$$H_{i,j} = LB_j + R * (UB_j - LB_j) \quad (20)$$

$H_{i,j}$ is the j th factor which Recognized

i th candidate solution

N is number of pupulation

m is number of variables

$R \in [0,1]$

The population companions of the Hamerkop in the proposed algorithm are identified through a population matrix.

$$H = \begin{bmatrix} H_1 \\ \vdots \\ H_i \\ \vdots \\ H_N \end{bmatrix}_{N \times m} = \begin{bmatrix} h_{1,1} & \cdots & h_{1,m} \\ \vdots & \ddots & \vdots \\ h_{N,1} & \cdots & h_{N,m} \end{bmatrix}_{N \times m} \quad (21)$$

H specify the Hamerkop population

Target functional vector is demarcated as,

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_i \\ \vdots \\ Z_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} Z(H_1) \\ \vdots \\ Z(H_i) \\ \vdots \\ Z(H_N) \end{bmatrix}_{N \times 1} \quad (22)$$

Z is target functional vector

The Hamerkop optimization algorithm plays out the enactment and scheme of the Hamerkop, while antagonizing and pestering the quarry to assess candidate explanations. This pestering scheme is completed through Rousing in the course of quarry, which serves as an exploration section, and the waterside is engaged as an exploitation section. In the Exploration section, Hamerkop identifies the spot of the quarry and then the passage in the course of the recognized region. The methodical simulation is demarcated as,

$$H_{i,j}^{HP_1} = \begin{cases} H_{i,j} + R * \begin{pmatrix} \text{Quarry}_j \\ -O * H_{i,j} \end{pmatrix}, \text{if } Z_{HP} < Z_i \\ H_{i,j} + R * \begin{pmatrix} H_{i,j} \\ -\text{Quarry}_j \end{pmatrix}, \text{Otherwise} \end{cases} \quad (23)$$

$H_{i,j}^{HP_1}$ is new location of Hamerkop

(initial exploration section)

$O \in [1,2]$

Quarry_j is spot of Quarry in jth magnitude

In the Hamerkop optimization algorithm, the new position is modernized as follows,

$$H_i = \begin{cases} H_i^{HP_1}, Z_i^{HP_1} < Z_i \\ H_i, \text{Otherwise} \end{cases} \quad (24)$$

$H_i^{HP_1}$ is new location of Hamerkop

$Z_i^{HP_1}$ is target functional value

In the exploitation section succeeding the Hamerkop dash the surface of the marine, they blow out their wings on the surface of the marine to direct the fishes up, and at that moment wrench the quarry over and done with oesophagus pack. This method hints at supplementary fish in the antagonized region to be ensnared by the Hamerkop. Scheme of this enactment of Hamerkop lees the Hamerkop optimization procedure to flock to heightened specifics in the pestering region. This enactment of Hamerkop in the passage of pestering is systematically premeditated as,

$$H_{i,j}^{HP_2} = H_{i,j} + R * (t - 1/T) * (2 * R - 1) * H_{i,j} \quad (25)$$

$H_i^{H_2}$ is new location of Hamerkop

$R = 0.20$

Active acquainting has also been cast off to acknowledge or abandon the new Hamerkop position, which is anticipated as,

$$H_i = \begin{cases} H_i^{HP_2}, Z_i^{HP_2} < Z_i \\ H_i, \text{Otherwise} \end{cases} \quad (26)$$

$H_i^{HP_2}$ is new location of Hamerkop

$Z_i^{HP_2}$ is target functional value

The process proceeds to the next repetition, and the divergent stages of the Hamerkop optimization procedure are repeated until completion.

$$H_i = \begin{cases} H_i^{HP_1}, Z_i^{HP_1} < Z_i \\ H_i, \text{Otherwise} \end{cases} \quad (27)$$

$H_i^{HP_1}$ is fresh position of Hamerkop

$Z_i^{HP_1}$ is objective functional value

This depiction of the hamerkop in the passageway of aggravation is methodically deliberated as,

$$H_{i,j}^{HP_2} = H_{i,j} + R * (t - 1/T) * (2 * R - 1) * H_{i,j} \quad (28)$$

$H_i^{H_2}$ is fresh position of Hamerkop

$R = 0.20$

Hamerkop optimization algorithm hybridized with Zeugodacus fulvoabdominalis optimization algorithm. This hybridization will increase the performance of exploitation. In Zeugodacus fulvoabdominalis, owing to their tremendous sight and conjoint compassionate deeds, Zeugodacus fulvoabdominalis will discover sustenance without exertion. Each Zeugodacus fulvoabdominalis upholds a track from its position, and the passage will be in the course of sustenance. A divergent class of Pong is matched, and a prime sustenance zone will be designated. At that moment, main attentiveness is designated as the optimal present position. Zeugodacus fulvoabdominalis' Optimization algorithm progresses the exploration to grasp the global optimum solution, primarily to avoid the local optimum solution.

$$\text{Min } F(Q) \text{ s.t. } z_j \in [\min_j, \max_j] \quad (29)$$

$j = 1, 2, 3, \dots, n$

Deliberation of pong in the Zeugodacus fulvoabdominalis optimization is defined as,

$$Q = (q_1, q_2, \dots, q_n)$$

Factors are primed, then the primary position (pp) is demarcated by,

$$\begin{cases} Q_{pp} = \min + (\max - \min) * rand() \\ R_{pp} = \min + (\max - \min) * rand() \end{cases} \quad (30)$$

By the chattels of the pong zeugodacus fulvoabdominalis reconnoitre, the sustenance and info will be passed to other Zeugodacus fulvoabdominalis. The new position of the Zeugodacus fulvoabdominalis is stimulated by,

$$\begin{cases} Q_i = Q_{pp} + rand() \\ R_i = R_{pp} + rand() \end{cases} \quad (31)$$

Starting from the initial position, the expanse (E) is computed as,

$$E_i = \sqrt{Q_i^2 + R_i^2} \quad (32)$$

Decree rate (D_i) of the pong deliberation in Zeugodacus fulvoabdominalis is the reciprocal of the expanse, and at that moment, the pong deliberation (P_i) is attained by,

$$\begin{cases} D_i = 1/e_i \\ P_i = F(D_i) \end{cases} \quad (33)$$

For all the zeugodacus fulvoabdominalis, select the least smell deliberation rate, and at that time, the drive to the analogous position is defined as,

$$\begin{cases} [Admirable Pong,] \\ [Admirable file] = Min(Pong) \\ \begin{cases} Q_{pp} = Q(Admirable file) \\ R_{pp} = R(Admirable file) \end{cases} \end{cases} \quad (34)$$

In the primary stage, Zeugodacus fulvoabdominalis will examine the sustenance in manifold ways, and they might be remote from the sustenance source, like sprinkling on the level,

$$\begin{cases} \begin{cases} Q_{pp} = rand(realm) \\ R_{pp} = rand(realm) \end{cases} \\ pp = \begin{cases} \sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i > 0 \\ -\sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i < 0 \end{cases} \\ Admirable Pong_p = F(pp) \end{cases} \quad (35)$$

Zeugodacus fulvoabdominalis will travel several ways for probing sustenance, and in the initial segment, the sustenance spring may be trivial,

$$\begin{cases} Q_t(i) = Q_p(i) + \varphi_y(i) \cdot rand() \\ R_t(i) = R_p(i) + \varphi_z(i) \cdot rand() \\ p_t = \begin{cases} \sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i > 0 \\ -\sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i < 0 \end{cases} \end{cases} \quad (36)$$

At that juncture, the t_{th} iterations steps (sp) are defined as,

$$sp_z^t(i) = Q_t(i) - Q_{t-1}(i) \quad (i = 1, 2, \dots, N) \quad (37)$$

In the plane, minor steps (s_{sp}) and big steps (l_{sp}) are noted,

$$\begin{aligned} \varphi_t(i) &= (l_{sp_t}(i) - s_{sp_t}(i)) \\ * \left[e^{\frac{sp_{t-1}(i) - s_{sp_t}(i)}{l_{sp_t}(i) - s_{sp_t}(i)}} - 1 \right] &+ s_{sp_t}(i) \end{aligned} \quad (38)$$

A standard distribution is employed to augment the spread

$$f(Q) = \frac{1}{\sqrt{2\pi}} \exp(-(Q - \varphi_t)^2) \quad (39)$$

The gradient decreases progressively by,

$$Gt_t(i) = \frac{No. of Zeugodacus fulvoabdominalis * \|Q_t(i) - Q_{t-1}(i)\|}{\sum_i \|Q_t(i)\|} \quad (40)$$

$$V(i) = \frac{Gt(i)}{\sum_i Gt(i)} \quad (41)$$

Memory step has been applied in the procedure.

$$MS_t = Q_t - Q_{t-1} \quad (42)$$

At that moment, the exploration procedure is defined as

$$\begin{cases} Q_{t+1} = Q_t + \lambda \cdot MS_t \cdot rand() \\ R_{t+1} = R_t + \lambda \cdot MS_t \cdot rand() \end{cases} \quad (43)$$

$$\lambda = \lambda_{max} \cdot \exp\left(\log\left(\frac{\lambda_{min}}{\lambda_{max}}\right) \cdot \frac{t}{t_{max}}\right) \quad (44)$$

Preceding iteration (μ), the Zeugodacus fulvoabdominalis will perform an examination.

$$f(z) = \begin{cases} 0 & z < \mu \\ [Memory \cdot 2 \cdot \left(\frac{1}{1+e^{\frac{z-\mu}{\mu}}} - \frac{1}{2}\right)] & z \geq \mu \end{cases} \quad (45)$$

Active acquainting has also been cast off to acknowledge or abandon the new Hamerkop position, which is premeditated as,

$$H_i = \begin{cases} H_i^{HP_2}, Z_i^{HP_2} < Z_i \\ H, \text{Otherwise} \end{cases} \quad (46)$$

$H_i^{HP_2}$ is fresh position of Hamerkop
 $Z_i^{HP_2}$ is objective functional value

1. Start
2. $H_{i,j} = LB_j + R * (UB_j - LB_j)$
3. $H = \begin{bmatrix} H_1 \\ \vdots \\ H_i \\ \vdots \\ H_N \end{bmatrix}_{N \times m} = \begin{bmatrix} h_{1,1} & \cdots & h_{1,m} \\ \vdots & \ddots & \vdots \\ h_{N,1} & \cdots & h_{N,m} \end{bmatrix}_{N \times m}$
4. $Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_i \\ \vdots \\ Z_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} Z(H_1) \\ \vdots \\ Z(H_i) \\ \vdots \\ Z(H_N) \end{bmatrix}_{N \times 1}$
5. Produce the location of the Hamerkop
6. Calculate the Target functional value
7. Arbitrarily produce the position of the quarry
8. $H_{i,j}^{HP_1} = \begin{cases} H_{i,j} + R * \begin{pmatrix} \text{Quarry}_j \\ -O * H_{i,j} \end{pmatrix} \\ , \text{if } Z_{HP} < Z_i \\ H_{i,j} + R * \begin{pmatrix} H_{i,j} \\ -\text{Quarry}_j \end{pmatrix} \\ . \text{Otherwise} \end{cases}$
9. $H_i = \begin{cases} H_i^{HP_1}, Z_i^{HP_1} < Z_i \\ H_i, \text{Otherwise} \end{cases}$
10. Employ the Exploration section
11. $H_{i,j}^{HP_2} = H_{i,j} + R * (t - 1/T) * (2 * R - 1) * H_{i,j}$
12. $H_i = \begin{cases} H_i^{HP_1}, Z_i^{HP_1} < Z_i \\ H_i, \text{Otherwise} \end{cases}$
13. $H_i = \begin{cases} H_i^{HP_2}, Z_i^{HP_2} < Z_i \\ H, \text{Otherwise} \end{cases}$
14. Hamerkop identifies the location of the quarry
15. Calculate the new position of Hamerkop
16. Streamline the ith population companion
17. Employ the Exploitation section
18. Calculate the new position of Hamerkop
19. Streamline the ith population companion
20. Calculate the new position of Hamerkop
21. Streamline the ith population companion
22. Define the examination of Zeugodacus fulvoabdominalis
23. $\begin{cases} Q_{pp} = \min + (\max - \min) * rand() \\ Q_{pp} = \min + (\max - \min) * rand() \end{cases}$
24. $\begin{cases} Q_i = Q_{pp} + rand() \\ R_i = R_{pp} + rand() \end{cases}$
25. $\begin{cases} [\text{Admirable Pong},] = \text{Min}(\text{Pong}) \\ \begin{cases} Q_{pp} = Q(\text{Admirable file}) \\ R_{pp} = R(\text{Admirable file}) \end{cases} \end{cases}$

26. $\begin{cases} Q_{pp} = rand(\text{realm}) \\ R_{pp} = rand(\text{realm}) \\ pp = \begin{cases} \sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i > 0 \\ -\sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i < 0 \end{cases} \\ \text{Admirable Pong}_p = F(pp) \end{cases}$
27. $\begin{cases} Q_t(i) = Q_p(i) + \varphi_y(i) * rand() \\ R_t(i) = R_p(i) + \varphi_z(i) * rand() \\ p_t = \begin{cases} \sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i > 0 \\ -\sqrt{Q_i^2 + R_i^2} \text{ if } Q_i + R_i < 0 \end{cases} \end{cases}$
28. $\varphi_t(i) = (l_{sp_t(i)} - s_{sp_t(i)})$
29. $* \left[e^{\frac{sp_{t-1}(i) - s_{sp_t(i)}}{l_{sp_t(i)} - s_{sp_t(i)}} - 1} \right] + s_{sp_t(i)}$
30. Modify the least value of time
31. $f(z) = \begin{cases} 0 & z < \mu \\ \left[\text{Memory} * 2 * \left(\frac{1}{1 + e^{\frac{z - \mu}{\mu}}} \right) - \frac{1}{2} \right] & z \geq \mu \end{cases}$
32. Output the most excellent solution
33. End

Results

The Hybrid Asiatic Cheetah - Gobi Bear Optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis Optimization (IHZFO) algorithm are substantiated in 7 benchmark functions (Yapıcı *et al.*, 2017). Table 1 displays the examination of results.

$$\begin{aligned} f_1(\text{parabola}) &= \sum_{i=1}^D x_i^2 \\ f_2(\text{Ackley}) &= -20 \exp \left\{ -0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2} \right\} \\ &\quad - \exp \left\{ \frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i) \right\} + 20 + e \\ f_3(\text{Rosen rock}) &= \sum_{i=1}^{D-1} \left\{ 100(x_{i+1} - x_i^2)^2 \right. \\ &\quad \left. + (x_i - 1)^2 \right\} \\ f_4(\text{Griewank}) &= \frac{1}{4000} \sum_{i=1}^D x_i^2 - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \\ f_5(\text{Hartman}) &= -\sum_{i=1}^4 c_i \exp \left[-\sum_{j=1}^3 \left(x_j - p_{ij} \right)^2 \right] \\ f_6(\text{Six - hump camel - back}) &= 4x_1^2 - 2.1x_1^4 \\ &\quad + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^3 \\ f_7(\text{Goldstein - Price}) &= \{1 + (x_1 + x_2 + 1)^2(19 - \\ &\quad 14x_1 + x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)\} \times \\ &\quad \left\{ \begin{aligned} &30 + (2x_1 - 3x_2)^2 \\ &((18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)) \end{aligned} \right\} \end{aligned}$$

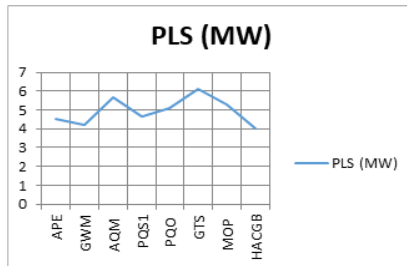
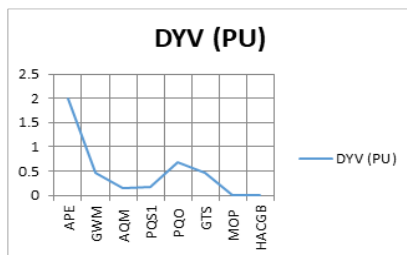
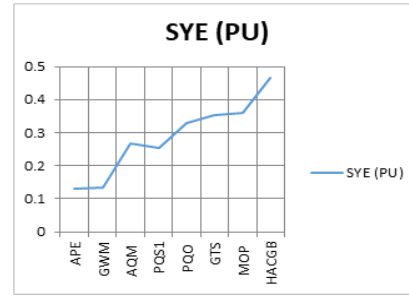
Table 1. HACGB, IHZFO results in 7 benchmark functions

FC	HSP (Yapıcı <i>et al.</i> , 2017)	EIP (Yapıcı <i>et al.</i> , 2017)	HACGB	IHZFO
1	0.8874	0.0026	0.0095	0.0095
2	0.0918	0.0125	0.0194	0.0194
3	22.9814	16.5622	16.491	16.491
4	1.1092 e-2	3.459 e-4	3.90 e-4	3.90 e-4
5	-3.8629	-3.8629	-3.8629	-3.8629
6	-1.0318	-1.0316	-1.0339	-1.0339
7	3.0280	3.0130	3.0137	3.0137

The Hybrid Asiatic cheetah - Gobi bear optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis optimization (IHZFO) algorithm are substantiated in the IEEE 30 bus system. Table 2, Figures 1 - 3 display the examination. PLS (MW) - power loss, DYV (PU) - Deviancy of voltage, SYE (PU) - Stability of voltage.

Table 2. HACGB, IHZFO examination in IEEE 30 bus

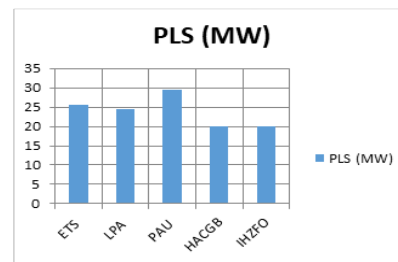
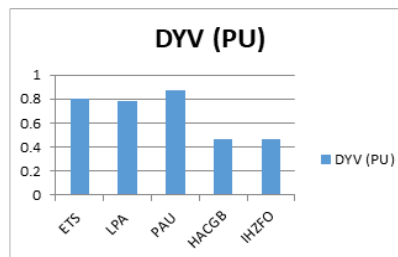
Technique	PLS (MW)	DYV (PU)	SYE (PU)
APE (Ali <i>et al.</i> , 2023)	4.5464	1.9889	0.1294
GWM (Varan <i>et al.</i> , 2023)	4.1781	0.4697	0.1323
AQM (Lian, 2022)	5.6614	0.1536	0.2683
PQS1 (Sahli <i>et al.</i> , 2022)	4.6304	0.1678	0.2524
PQO (Hasanien <i>et al.</i> , 2024)	5.0763	0.6828	0.3297
GTS (Gil <i>et al.</i> , 2024)	6.1300	0.4710	0.3521
MOP (In <i>et al.</i> , 2024)	5.3048	0.4632	0.3614
HACGB	4.0048	0.0074	0.4667
IHZFO	4.0042	0.0071	0.4663

**Figure 1. HACGB, IHZFO examination in IEEE 30 bus****Figure 2. Deviancy of voltage (DYV (PU)) - IEEE 30 bus system****Figure 3. Stability of voltage (SYE (PU)) - IEEE 30 bus system**

The Hybrid Asiatic cheetah - Gobi bear optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis optimization (IHZFO) algorithm are substantiated in the IEEE 57 bus system. Table 3 and Figures 4 - 6 display the examination results.

Table 3. HACGB, IHZFO examination in IEEE 57 bus

Technique	PLS (MW)	DYV (PU)	SYE (PU)
ETS (Shaheen <i>et al.</i> , 2023)	25.4963	0.799021	0.3129
LPA (Khan <i>et al.</i> , 2024)	24.4198	0.7844	0.3512
PAU (Rao <i>et al.</i> , 2024)	29.535	0.8725	0.3791
HACGB	20.01969	0.46190	0.4639
IHZFO	20.01965	0.46187	0.4636

**Figure 4. Power loss (PLS (MW)) - IEEE 57 bus system****Figure 5. Deviancy of voltage (DYV (PU)) - IEEE 57 bus system**

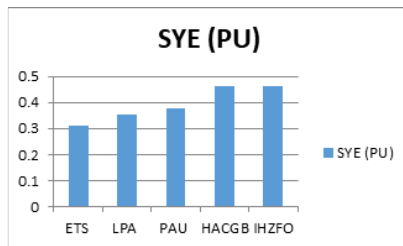


Figure 6. Stability of voltage (SYE (PU)) - IEEE 57 bus system

Computational time of the Hybrid Asiatic cheetah - Gobi bear optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis optimization (IHZFO) algorithm are presented in Table 4 and Figure 7.

Table 4. HACGB, IHZFO Computational time

Method	30 BUS T(S)	57BUS T(S)
HACGB	14.90	19.91
the IHZFO	14.88	19.86

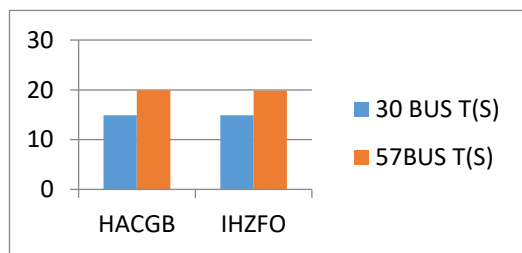


Figure 7. Computational time of HACGB optimization and IHZFO algorithm

Conclusion

The Hybrid Asiatic cheetah - Gobi bear optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis optimization (IHZFO) algorithm effectively reduced the loss. The Asiatic cheetah optimization algorithm is based on the stalking approach of the Asiatic cheetah, which involves a sequence of activities: probing for prey, patiently waiting for the optimal moment to attack, rapidly initiating the attack, retreating from the prey, and returning to the habitat. During the period of probing for prey, each Asiatic cheetah pursues different prey positions, indicating the key decision parameters that influence the population's conditions.

The Gobi bear optimization algorithm is grounded on the searching performance of the Gobi bear. Numerous intellectual activities of the Gobi bear, such as tracking the cluster, detecting food sources, and navigating the terrain, are considered in the design. Gobi bear utilizes lever odour marking and snuffling activities in the habitat. The Hamerkop optimization algorithm plays out the enactment and scheme of Hamerkop, while antagonizing and pestering the quarry to assess candidate explanations. In Zeugodacus fulvoabdominalis, owing to their very tremendous sightedness and conjoint compassionate deeds Zeugodacus fulvoabdominalis will discover the sustenance deprived of exertion. Each Zeugodacus fulvoabdominalis upholds a track from its position, and the passage will be in the course of sustenance. A divergent class of Pong is matched, and a prime sustenance zone will be designated. At that moment, main attentiveness is designated as the optimal present position. The Hybrid Asiatic Cheetah - Gobi Bear Optimization (HACGB) algorithm and the Integrated Hamerkop - Zeugodacus fulvoabdominalis Optimization (IHZFO) algorithm are substantiated using seven benchmark functions and the IEEE 30 and 57 bus systems.

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