

# ENHANCED EQUUS FERUS PRZEWALSKII OPTIMIZATION AND ADVANCED OSTEOLAEMUS SEARCH ALGORITHM

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## Abstract

We apply the enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and the advanced Osteolaemus search optimization (AOSO) algorithm to solve true power loss reduction problems. Equus Ferus Przewalskii tends to pursue and run in its environment. As a result, the adult Equus Ferus Przewalskii and steeds adopt an arbitrary course. At that juncture, a vibrant inertia weight approach is presented to the oasis, and the results will be valuable to poise the exploration and exploitation. The Equus Ferus Przewalskii optimization algorithm is combined with the Anarchias seychellensis and Peacock hind's teamwork-based optimization algorithm to improve the exploration ability of the process. The Osteolaemus search optimization algorithm imitates the two key phases of Osteolaemus behavior—ringing and stalking. Osteolaemus have flawless nocturnal vision and are primarily nocturnal stalkers. Osteolaemus employ the paleness of victim animals for their sustenance. Osteolaemus are ensnaring slayers, searching for nearby fish or terrestrial animals before proceeding to their next meal. Osteolaemus can track prey over short distances, even out of aquatic conditions. Osteolaemus have double passages in the course of the ringing; tall marching and tummy marching. The osteolaemus search optimization algorithm has assimilated the advanced features of the cryptoprocta search optimization algorithm. This assimilation will upgrade the exploitation competence of the process substantially. The Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and the advanced Osteolaemus search optimization (AOSO) algorithm have been tested successfully on 7 standard functions, as well as the IEEE 30, 57, and 118 bus systems, and the Grid 220 kV system.

**Keywords:** Anarchias Seychellensis; Cryptoprocta; Equus Ferus Przewalskii; Osteolaemus; Peacock Hind

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## Introduction

The Enhanced Equus ferus przewalskii Optimization (EEPO) algorithm and the Advanced Osteolaemus Search Optimization (AOSO) algorithm are used to reduce true power loss, as demonstrated in various studies including EPU (Pg *et al.*, 2022), MCO (Abd-El Wahab *et al.*, 2022), EOI (Habib Khan *et al.*, 2022), ATN (Ali *et al.*, 2023), GIA (Varan *et al.*, 2023), PSP1 (Lian, 2022), BRT (Sahli *et al.*, 2022), ZPT (Hasanien *et al.*, 2024), CON (Shaheen *et al.*, 2023), and SARANI (Kanagasabai, 2024).

### Equus Ferus Przewalskii Optimization Algorithm

The *Equus ferus przewalskii* optimization algorithm imitates the actions of Przewalski's horse. The algorithm utilizes the natural behavior of *Equus ferus przewalskii* (Flack *et al.*, 2024) in its design. The algorithm incorporates the random movement approach and the competition for oasis mechanism. The random movement approach is employed to balance exploration and exploitation, and the competition for oasis mechanism is designed to enhance exploitation performance. Furthermore, a dynamic inertia weight approach is employed to attain the optimal solution.

In their natural environment, Przewalski's horses exhibit running and chasing behaviors. Accordingly, a random movement approach is applied to adult horses and stallions. A dynamic inertia weight approach is introduced at the oasis, which helps balance exploration and exploitation. The competition for oasis mechanism is designed specifically for stallions.

In the wild, Przewalski's horses frequently run and chase each other. Inspired by this behavior, the random movement approach is designed for both adult horses and stallions. The dynamic inertia weight approach has been incorporated into the procedure when stallions discover a superior oasis.

### Hybrid Enhancement with Fish Cooperative Behavior

The *Equus ferus przewalskii* optimization algorithm is hybridized with an optimization algorithm based on the cooperative actions of *Anarchias seychellensis* (moray eel) and peacock hind to enhance the exploration capability of the process. This optimization algorithm is created by mimicking how these fish cooperate and search for food in the ocean.

In natural marine environments, there are complex interactions among similar or different biological species. Peacock hinds signal *Anarchias*

*seychellensis* to hunt prey together in cooperative mode. Peacock hinds hunt prey in seawater, while parrotfish hide in corals to avoid being consumed by predators. *Anarchias seychellensis* emerge from ridge crevices and attempt to encircle the prey in their hiding places. At this point, parrotfish flee from the corals, and the group of peacock hinds and *Anarchias seychellensis* encircle the prey. A coordinated group attack is then initiated on the encircled prey. This cooperative behavior between *Anarchias seychellensis* and peacock hinds leads to successful hunting.

The peacock hind generates a signal to *Anarchias seychellensis* about parrotfish hiding in corals. Subsequently, *Anarchias seychellensis* encircles the hiding places in the corals, triggering the parrotfish to flee. As soon as the parrotfish begin to move in open waters, a group of peacock hinds, accompanied by *Anarchias seychellensis*, encircle and attack them. This collaborative action between *Anarchias seychellensis* and peacock hinds has been mathematically formulated for the optimization algorithm.

### Osteolaemus Search Optimization Algorithm

The *Osteolaemus* search optimization algorithm is developed by emulating the hunting behavior of dwarf crocodiles (*Osteolaemus*). The algorithm mimics two key phases of *Osteolaemus* behavior: circling and stalking. *Osteolaemus* (Smolensky *et al.*, 2023) have excellent nocturnal vision and are primarily nocturnal hunters. They exploit the limited night vision of prey animals for their survival. *Osteolaemus* are ambush predators, waiting for nearby fish or terrestrial animals and then lunging to attack. They can track prey over short distances, even outside aquatic environments.

The exploration phase incorporates a designed circling action. During the circling action, *Osteolaemus* performs two distinct movements: tall marching and belly crawling. These movements represent different strategies that contribute to the exploration search. These movements do not allow them to reach the target prey directly due to their indirect approach, unlike the stalking phase. Therefore, the exploration search covers an extensive search region and can discover promising zones after multiple iterations.

In the exploitation phase, stalking by *Osteolaemus* employs two strategies: stalking synchronization and collaboration. These strategies represent different intensification methods that contribute to the exploitation search (local mode).

These strategies allow them to reach the target prey directly due to their focused approach, distinct from the circling method.

### Integration with Cryptoprocta Search Optimization

Migration attributes from an advanced *Cryptoprocta* search optimization algorithm have been assimilated into the *Osteolaemus* search optimization algorithm. This integration substantially upgrades the exploitation capability of the process. The *Cryptoprocta* search optimization algorithm is designed by emulating the hunting activity of the fossa (*Cryptoprocta*) in its natural environment.

In hunting activities, *Cryptoprocta* executes a two-phase strategy. First, it identifies the prey and makes preliminary adjustments, then slowly tracks the prey, and finally attacks when conditions are favorable. In the exploration phase, preliminary adjustments by *Cryptoprocta* are defined mathematically.

### Enhanced Equus Ferus Przewalskii Optimization Algorithm

The *Equus ferus przewalskii* optimization (EPO) algorithm imitates the actions of Przewalski's horse. The natural behavior of *Equus ferus przewalskii* is utilized to design the algorithm. The design incorporates both the random movement approach and the competition for oasis mechanism. The random movement approach is employed to balance exploration and exploitation, while the competition for oasis mechanism is designed to enhance exploitation performance. Moreover, the dynamic inertia weight method is utilized to achieve the optimal solution.

Typically, *Equus ferus przewalskii* can be divided into two distinct classes based on their group affiliation. Przewalski's horses live in herds of different age groups, such as juveniles, stallions, and mares. Stallions and mares coexist and interact with each other during foraging. When they mature, *Equus ferus przewalskii* move away from their natal herds and join other herds to form their own groups. This behavior prevents inbreeding between stallions and siblings.

In foraging activities, most adult *Equus ferus przewalskii* spend their lives grazing close to their herd. In the foraging phase, the stallion's location is positioned at the center of the foraging zone.

$$Z_{c,j}^i = 2Y \cos(2\pi \cdot \text{Rand} \cdot Y) \times (S_{c,j} - Z_{c,j}^i) + S_{c,j} \quad (1)$$

where  $Z_{c,j}^i$  specify the  $i$ th cluster associate  
 $S_{c,j}$  define the steeds position in the  $j$ th cluster

$$R \in [-2, 2]$$

$$U = \overrightarrow{\text{Rand}}_1 < H, V = (U == 0)$$

where  $H$  is decreasing factor in linear mode

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

$$\overrightarrow{\text{Rand}}_1 \in [0, 1]$$

$$Y = \text{Rand}_2 \odot V + \overrightarrow{\text{Rand}}_3 \odot (\sim V) \quad (2)$$

$$\text{Rand}_2 \in [0, 1]$$

$$\overrightarrow{\text{Rand}}_3 \in [0, 1]$$

$$H = 1 - t/T$$

where  $t, T$  are present and maximum iterations  
 $Y$  define the adaptive factor

*Equus ferus przewalskii* Coupling Performance is an exclusive activity and is separately grown up. *Equus ferus przewalskii* from their original clusters is previous to their attainment of sexual maturity and coupling. The formulation has utilized *Equus ferus przewalskii*'s learning capacity as they mature.

$$Z_{c,k}^a = \text{Cr}(Z_{c,i}^m, Z_{c,j}^n) \quad (3)$$

where  $Z_{c,k}^a$  location of *Equus ferus przewalskii* in cluster  $a$  and it created by  $m$  and  $n$  cluster

$\text{Cr}$  indicate the crossover

$$i \neq j \neq k$$

$$m = n = \text{end}$$

Cluster frontrunners - steeds will prime other cluster associates to an appropriate zone (oasis). Cluster frontrunners (steeds) will also contend for the oasis, leading the foremost cluster to engage the oasis first.

$$\overrightarrow{\text{Steed}}_{c,j} = \begin{cases} 2Y \cos(2\pi \cdot \text{Rand} \cdot Y) * (PO - \text{Steed}_{c,j}) + PO, & \text{if } R > 0.50 \\ 2Y \cos(2\pi \cdot \text{Rand} \cdot Y) * (PO - \text{Steed}_{c,j}) - PO, & \text{if } R \leq 0.50 \end{cases} \quad (4)$$

where  $PO \rightarrow$  the location of oasis  
 $\overrightarrow{\text{Steed}}_{c,j} \rightarrow$  candidate location  
 $\text{Steed}_{c,j} \rightarrow$  current position

Initially, frontrunners are nominated arbitrarily. Subsequently, frontrunners are designated based on their fitness values. The interchange among forerunner locations and other entities is defined as,

$$\text{Steed}_{c,j} = \begin{cases} Z_{c,j}^i, & \text{if } f(Z_{c,j}^i) < f(\text{Steed}_{c,j}) \\ \text{Steed}_{c,j}, & \text{if } f(Z_{c,j}^i) \geq f(\text{Steed}_{c,j}) \end{cases} \quad (5)$$

where  $f(Z_{c,j}^i)$  specify the fitness value of Grown up Equus Ferus Przewalskii  
 $f(Steed_{c,j})$  define the fitness value of the steed

$$\overline{Steed}_{c,j} = \begin{cases} 2Y \cos(2\pi \cdot \text{Rand} \cdot Y) * (PO - Steed_{c,j}) \\ \quad + \varphi * PO, \\ \quad \text{if } R_3 > 0.50 \\ PO - Y * (Steed_{c,j} \cdot O_1 - Steed_{c,j} \cdot O_2), \\ \quad \text{if } R_3 \leq 0.50 \end{cases} \quad (10)$$

Primarily, *Equus ferus przewalskii* in the environment has a habit of pursuit and running. Consequently, the adult *Equus ferus przewalskii* and steeds adopt an arbitrary course approach. At that juncture, a vibrant inertia weight approach is presented to the oasis, and the results will be valuable to poise the exploration and exploitation. The rivalry for the oasis system is intended for horses.

In the landscape, *Equus ferus przewalskii* exhibits affectionate behavior, running and pursuing each other. This approach stimulates both the grown-up *Equus ferus przewalskii* and steeds to adopt an arbitrary course. The location modernizing formulation is defined as,

$$Z_{c,j}^i \text{ or } \overline{Steed}_{c,j} = \text{minimum} + (\text{maximum} - \text{minimum}) * R \quad (6)$$

where  $\text{maximum}$  and  $\text{minimum}$  are limits value of arbitrary course approach=0.10

The vibrant inertia weight approach has been used in the procedure and steeds discovers a superior oasis, then the weight formulation is defined as,

$$\varphi = \begin{cases} \varphi \min + (\varphi \max - \varphi \min) * \frac{f(t)i - f(t)\min}{f(t)\text{mean} - f(t)\min}, \\ \quad \text{if } f(t)i \leq f(t)\text{mean} \\ \varphi \max, \text{if } f(t)i > f(t)\text{mean} \end{cases} \quad (7)$$

where  $\varphi$  specify the vibrant inertia weight approach

$$\overline{Steed}_{c,j} = 2Y \cos(2\pi \cdot \text{Rand} \cdot Y) * (PO - Steed_{c,j}) + \varphi * PO \quad (8)$$

where  $f(t)i \rightarrow$  fitness value of present steed  
 $f(t)\text{mean} \rightarrow$  fitness value of all steeds

Furthermore, the oasis can be discovered by two steeds concurrently. At that juncture, competition amongst steeds for the oasis will occur. Consequently, to further progress the solution superiority, the rivalry for the oasis is incorporated in the procedure.

$$\overline{Steed}_{c,j} = PO - Y * (Steed_{c,j} \cdot O_1 - Steed_{c,j} \cdot O_2) \quad (9)$$

$O_1, O_2 \in [-1, 1]$

Then the lead frontrunner steed is defined as,

The Equus Ferus Przewalskii optimization algorithm is combined with the Anarchias seychellensis and Peacock hind's teamwork-based optimization algorithm to improve the process's ability to explore. The Anarchias seychellensis and Peacock hind's cooperative actions-based optimization algorithm is designed by mimicking how Anarchias seychellensis and Peacock hind work together and search for resources in the ocean. In natural surroundings, there are multifaceted collaborations among biotic classes that are analogous or varied. Peacock hinds and Anarchias seychellensis cooperate to stalk prey together. Peacock hind stalk the prey in seawater, and parrotfishes are rawhide in corals to evade being consumed by the hunters. Anarchias seychellensis will gaffe from the side of the ridge fissures and attempts to enfold the victim in hovels. At that juncture, parrotfishes will flee the corals, and then the group of Peacock hinds, Anarchias seychellensis, will encircle the prey. Immediately will be group attack will be initiated over the encircled prey. This cooperative behaviour between Anarchias seychellensis and the Peacock hind leads to successful hunting. The peacock hind group assesses the parrotfishes' position to determine preeminent fitness. The preliminary population arbitrarily designates Anarchias seychellensis, a quiescent adjoining species, at its location. Dual parameters  $Q_1$  and  $Q_2$  Which has arbitrary values larger than one or less than that is to thrust the examination agent away from the preeminent location. As an alternative to a preeminent examination agent, an arbitrary examination agent is set to modernize the location of an examination agent in the search segment. This specific action is modelled in the exploration section.

$$\vec{Y}_i^{t+1} = \vec{Y}_A + \vec{Q}_1 \cdot |\vec{Y}_i^t - \vec{Q}_2 \cdot \vec{Q}_1| \quad (11)$$

$A \rightarrow \text{Arbitrary}$

$$\vec{Y}_i^{t+1} = \vec{Y}_i^{t+1}, \text{if } f(\vec{Y}_i^{t+1}) > \vec{Y}_i^{t+1} \quad (12)$$

$$\begin{aligned} \vec{Q}_1 &= 2c \cdot a_1 - c \\ \vec{Q}_2 &= 2a_2 \\ a_1, a_2 &\in [0, 1] \\ c &= \text{decrease from 2 to 0 as iterations grows} \\ c &= 2 - 2 * \left( \frac{t}{\text{max iter}} \right) \end{aligned}$$

Peacock hinds share their locations of bout and annotations using cranium trembling. Peacock

hinds, when predominantly in a starving period, parrotfishes flee from the rawhide in corals, plunge to the adjacent *Anarchias seychellensis* in its daylight whacking place, at that juncture Peacock hinds perform an eccentric cranium trembling hop and fluttering their dorsal fin.

$$\begin{aligned} \overline{YM}_i^t &= Q_2 \cdot \overline{YE}_i^t, \text{ if } a_3 \leq S \\ a_3 &= 100 * A \\ A &\rightarrow \text{Arbitrary} \\ S &\rightarrow \text{starving period} \\ S &= 100 * \left( \frac{t}{\text{max iter}} \right) \\ Q_1 &\in [-c, c] \\ Q_2 &\in [0, 2] \end{aligned} \quad (13)$$

Peacock hind engenders the signal to *Anarchias seychellensis* about the parrotfishes, which are rawhide in corals. Then, sequentially, *Anarchias seychellensis* encircles the hovels of the rawhide in corals, which trigger the parrotfishes to flee from the rawhide in corals. Once the parrotfishes start moving in the oceanic waters group of Peacock hinds, *Anarchias seychellensis*, will encircle and attack the parrotfishes. This specific action is modelled in the exploitation section.

$$\begin{aligned} Y_1 &= db^{a_4} \cdot \sin(2\pi a_4) \cdot \vec{Q}_1 \cdot |\overline{YM}_i^t - \overline{YN}_i^t| + \overline{YM}_i^t \quad (14) \\ a_4 &= (c - 2) \cdot a_1 + 2 \\ Y_2 &= \overline{YE}_i^t + \vec{Q}_1 \cdot |\overline{YE}_i^t - \overline{YN}_i^t| \\ \vec{Y}_i^{t+1} &= \frac{0.9Y_1 + 0.2Y_2}{2}, \text{ if } z < 0.5 \\ \vec{Y}_i^{t+1} &= \frac{0.2Y_1 + 0.9Y_2}{2}, \text{ if } z \geq 0.5 \end{aligned}$$

#### Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm

- a. Begin
- b. Create the Equus Ferus Przewalskii population
- c. Compute the linear decreasing factor
- d. Calculate the adaptive factor
- e.  $Y = Rand_2 \odot V + \overrightarrow{Rand_3} \odot (\sim V)$
- f. *For the quantity of steeds*
- g. *For the quantity of Grown up Equus Ferus Przewalskii*
- h. *If Random > Probability of crossover*
- i. Modernize the location of Grown up Equus Ferus Przewalskii
- j.  $Z_{c,j}^i = 2Y \cos(2\pi \cdot Rand \cdot Y) * (S_{c,j} - Z_{c,j}^i) + S_{c,j}$
- k. *Else if Random > probability of arbitrary course approach*
- l. Streamline the position of Grown up Equus Ferus Przewalskii
- m.  $Z_{c,k}^a = Cr(Z_{c,i}^m, Z_{c,j}^n)$
- n. *Or else*

- o. Update the position of Grown up Equus Ferus Przewalskii
- p.  $Z_{c,j}^i \text{ or } \overline{Steed}_{c,j} = \text{minimum} + (\text{maximum} - \text{minimum}) * R$
- q. *if Random > probability of arbitrary course approach*
- r. *if Random > 0.50*
- s. Create the candidate location for the steed
- t.  $\overline{Steed}_{c,j} = PO - Y * (\overline{Steed}_{c,j} \cdot O_1 - \overline{Steed}_{c,j} \cdot O_2)$
- u. *Or else*
- v. Produce the location of the steed
- w.  $\overline{Steed}_{c,j} = 2Y \cos(2\pi \cdot Rand \cdot Y) * (PO - \overline{Steed}_{c,j}) + \phi * PO$
- x. Else
- y. Engender the position of Steed
- z.  $Z_{c,j}^i \text{ or } \overline{Steed}_{c,j} = \text{minimum} + (\text{maximum} - \text{minimum}) * R$
- aa. End if
- bb. If the candidate location of the steed is better, then
- Swap the location of the steed using the candidate position
- cc. Interchange Grown up Equus Ferus Przewalskii and steeds position
- dd. *Define the location of Anarchias seychellensis and Peacock hinds*
- ee.  $\vec{Y}_i^{t+1} = \vec{Y}_i^t + \vec{Q}_1 \cdot |\vec{Y}_i^t - \vec{Q}_2 \cdot \vec{Q}_1|$
- ff.  $\overline{YE}_i^{t+1} = \vec{Y}_i^{t+1}, \text{ if } f(\vec{Y}_i^{t+1}) > \overline{YE}_i^{t+1}$
- gg. Define the trembling factor
- hh.  $\overline{YM}_i^t = Q_2 \cdot \overline{YE}_i^t, \text{ if } a_3 \leq S$
- ii. Compute the attack factor
- jj.  $Y_1 = db^{a_4} \cdot \sin(2\pi a_4) \cdot \vec{Q}_1 \cdot |\overline{YM}_i^t - \overline{YN}_i^t| + \overline{YM}_i^t$
- kk.  $Y_2 = \overline{YE}_i^t + \vec{Q}_1 \cdot |\overline{YE}_i^t - \overline{YN}_i^t|$
- ll.  $\vec{Y}_i^{t+1} = \frac{0.9Y_1 + 0.2Y_2}{2}, \text{ if } z < 0.5$
- mm.  $\vec{Y}_i^{t+1} = \frac{0.2Y_1 + 0.9Y_2}{2}, \text{ if } z \geq 0.5$
- nn.  $t = t + 1$
- oo. End

#### Advanced Osteolaemus Search Optimization Algorithm

The stalking behavior of *Osteolaemus* inspires the *Osteolaemus* search optimization algorithm. The algorithm mimics the two key phases of *Osteolaemus* behavior, ringing and stalking. *Osteolaemus* have flawless nocturnal vision and are primarily nocturnally stalkers. *Osteolaemus* employ the paleness (glum nocturnal vision) of victim animals for their sustenance. *Osteolaemus* are

ensnaring slayers, looking for neighbouring fish or terrestrial animals, and then consecutively out to bout. Osteolaemus can track prey over short distances, even out of aquatic conditions. When an Osteolaemus passes rapidly, it preserves its limbs in a square and upright condition beneath its body (tall march). This tall march permits Osteolaemus to pass at a tremendous speed. Osteolaemus possess certain progressive intellectual abilities. Osteolaemus can identify and employ outlines of victim performance, such as when the victim approaches the waterway to drink repeatedly. Osteolaemus are progressive stalkers: they collaborate as a team to hunt their prey. Osteolaemus carry out stalking in a supportive manner, grounded on synchronization and teamwork. Synchronized stalking is a refined form of cooperative stalking, in which specific slayers associate in each other's engagements, attuned to the target victim throughout systematized stalking. Osteolaemus stalks a squad and moves in collaboration mode among dissimilar entities with altered parts. Osteolaemus search optimization algorithm starts with a fixed number of candidate solutions as follows,

$$O = \begin{bmatrix} o_{1,1} & \cdots & o_{1,n} \\ \vdots & \ddots & \vdots \\ o_{N,1} & \cdots & o_{N,n} \end{bmatrix} \quad (15)$$

$O \rightarrow$  fixed number of candidate solutions  
 $N, n$  define the solution candidate number and dimension of the problem

$$o_{ij} = \text{Random} \cdot (\max - \min) + \max \quad (16)$$

$\text{Random} \in [0,1]$   
 $\max$  and  $\min$  define the limits

The algorithm explores and designs the ringing action. Osteolaemus have double passages in the course of the ringing; tall marching and tummy marching. These passages refer to dissimilar sways, which contribute to the exploration search. Osteolaemus passages (tall marching and tummy marching) will not allow them to reach their target prey because they make too much noise, unlike other hunting methods. Therefore, the exploration search determines an extensive search region; it can discover the compactness zone, perhaps after numerous activities. In addition, the exploration methods (tall marching and tummy marching) are used at this stage of optimization to support the extra part, moving through the exploration process with a broad and detailed investigation. The Osteolaemus search optimization algorithm can be transferred among (exploration and stalking, exploitation) examination segments; this alteration among numerous activities is completed based on the conditions. The exploration mode of the algorithm

is to explore the search space and find a better solution based on double key search approaches (tall marching and tummy marching strategies).

*Tall marching is defined as,  $t \leq T/4.0$*

*Tummy marching is defined as,  $t \leq 2.0 \cdot T/4.0$  and  $t > T/4.0$*

The above tall marching and tummy marching stratagem will be gratified for nearly the partial quantity of exploration iterations (tall marching) and additional partial for the tummy marching. The location modernizing for the exploration segment is defined as diminishing.

$$o_{i,j}(t+1) = \begin{cases} L_j(t) \cdot -\varphi_{(i,j)}(t) \cdot \alpha - O_{(i,j)}(t) \\ \quad * \text{random}, t \leq T/4.0 \\ L_j(t) \cdot o_{(R_1,j)} \cdot E(t) \\ \quad * \text{random}, t \leq 2 \cdot T/4.0 \\ \quad \text{and } t > T/4.0 \end{cases} \quad (17)$$

$L_j(t) \rightarrow$  excellent solution obtained so far

$\text{Random} \in [0,1]$

$t, T$  are the current and maximum iteration

$\varphi_{(i,j)}(t)$  indicate the stalking operator

$\alpha$  is to regulate the exploration precision  $\rightarrow 0.1$

$R_1 \in [1, N]$

$E \rightarrow$  decreases between 2 and  $-2$

$$\varphi_{(i,j)}(t) = L_j(t) * U_{(i,j)} \quad (18)$$

$U_{(i,j)} \rightarrow$  difference

between best and current position

$$D_{(i,j)}(t) = \frac{L_j(t) - o_{(R_2,j)}}{L_j(t) + \varepsilon} \quad (19)$$

$R_2 \in [1, N]$

$$E(t) = 2.0 * R_3 * \left(1 - \frac{1}{T}\right)$$

$R_3 \in [-1,1]$

$$U_{(i,j)} = \beta + \frac{\varphi_{(i,j)} - A(o_i)}{L_j(t) * (\max_j - \min_j) + \varepsilon}$$

$A(o_i)$  specify the average location

$\beta$  is to regulate the exploration precision  $\rightarrow 0.1$

$$A(o_i) = \frac{1}{n} \sum_{j=1}^n o_{(i,j)}$$

In exploitation performance, stalking of Osteolaemus has double stratagems - stalking synchronization and collaboration. These stratagems refer to dissimilar deepening methods, which pledge to the exploitation quest (local mode). Osteolaemus stratagems; stalking synchronization and collaboration will permit them to reach the target victim straightforwardly, owing to their escalation, distinct from the ringing method. Therefore, the exploitation pursuit discerns the near optimal solution, perhaps afterwards of numerous activities. Moreover, the exploitation method functions at this phase of optimization to demeanour a sensitivity analysis near the optimal solution and highlight communiqué amongst them.

stalking synchronization is defined as,  $t \leq 3.0 \cdot T/4.0$  and  $t > 2.0 \cdot T/4.0$

stalking collaboration is defined as,  $t \leq T$  and  $t > 3.0 \cdot T/4.0$

$$o_{i,j}(t+1) = \begin{cases} L_j(t) * U_{(i,j)} * \text{random}, & t \leq 3.0 \cdot T/4.0 \text{ and } t > 2.0 \cdot T/4.0 \\ L_j(t) \cdot \varphi_{(i,j)}(t) \cdot \varepsilon - O_{(i,j)}(t) * \text{random}, & t \leq T \text{ and } t > 3.0 \cdot T/4.0 \end{cases} \quad (20)$$

$L_j(t) \rightarrow$  excellent solution obtained so far

Random  $\in [0,1]$

$t, T \rightarrow$  current and maximum iteration

$\varphi_{(i,j)}(t)$  indicate the stalking operator

$\alpha$  is to regulate the exploration precision  $\rightarrow 0.1$

$R_1 \in [1, N]$

Migration attributes Advanced Cryptoprocta search optimization algorithm has been assimilated into the Osteolaemus search optimization algorithm. This assimilation will upgrade the exploitation competence of the process substantially. Cryptoprocta search optimization algorithm is designed by emulating the hunting activity of the cryptoprocta in its environment (Hawkins *et al.*, 2008). In the hunting activity, cryptoprocta executes a twofold strategy. In the exploration segment, preliminary adjustments of the cryptoprocta are defined mathematically. In the exploitation segment, cryptoprocta's change of location in response to the prey movement is scientifically modelled. Each location of the cryptoprocta summarizes a candidate solution in the search space.

$$c_{i,j} = lb_j + P(ub_j - lb_j) \quad (21)$$

$max_j, min_j \rightarrow$  limits

$P \in [0,1]$

In the preliminary segment of the cryptoprocta search optimization algorithm, the locations of the population associates inside the problem-solving region are rationalized by pretending the cryptoprocta attack on the prey. For each cryptoprocta, the locations of other population associates with superior objective functional standards are considered as prey locations inside the environment. Subsequently, the prey for each cryptoprocta is defined by equaling objective functional standards.

$$\begin{aligned} H_i &= \{E_k, F_k > F_i\} : \forall k = 1, 2, 3, \dots, N, i = 1, 2, \dots, N \\ H_i &\rightarrow \text{prey location} \\ E_{i,j}^{L1} &= E_{i,j} + P \cdot (X_{i,j} - D_1 \cdot E_{i,j}) \\ E_{i,j}^{L1} &\rightarrow \text{new location of } i\text{th cryptoprocta} \\ X_{i,j} &\rightarrow \text{prey chosen by } i\text{th cryptoprocta} \\ P &\in [0,1] \\ D_1 &\in \{1,2\} \\ E_i &= \begin{cases} E_i^{L1}, F_i^{L1} \leq F_i \\ E_i, \text{otherwise} \end{cases} \end{aligned} \quad (22)$$

Depending on the prey's movement, the cryptoprocta will adjust its location continuously.

$$\begin{aligned} E_{i,j}^{L2} &= E_{i,j} + P \cdot (Z_j - D_2 \cdot E_{i,j}) \\ E_{i,j}^{L2} &\rightarrow \text{new location of } i\text{th cryptoprocta} \\ Z_j &\rightarrow \text{minor movement of the prey} \\ P &\in [0,1] \\ D_2 &\in \{1,2\} \\ E_i &= \begin{cases} E_i^{L2}, F_i^{L2} \leq F_i \\ E_i, \text{otherwise} \end{cases} \end{aligned} \quad (23)$$

Locations of the populace associates are modernized by pretending the cryptoprocta's actions of continuously following the prey. Once the feasible conditions are there inside the region where the prey is located, then cryptoprocta will attack the prey immediately. The exploitation segment of the algorithm formulates these actions scientifically.

$$\begin{aligned} E_{i,j}^{L3} &= E_{i,j} + (1 - 2 \cdot P) \cdot \frac{ub_j - lb_j}{t} \\ E_{i,j}^{L3} &\rightarrow \text{new location of } i\text{th cryptoprocta} \\ P &\in [0,1] \\ E_i &= \begin{cases} E_i^{L3}, F_i^{L3} \leq F_i \\ E_i, \text{otherwise} \end{cases} \end{aligned} \quad (24)$$

When predators of cryptoprocta enter the environment, the cryptoprocta immediately flees, resulting in a chaotic condition. This aspect is considered in the mathematical design of the algorithm. Logistic chaos mapping (Alrubaie *et al.*, 2023) is delineated as

$$\begin{aligned} A_{n+1} &= zA_n(1 - A_n) \\ z &\in [0,4] ; z, B_0 \in [0,1] \forall n \in \{0,1,\dots\} \\ B_n &\leq \frac{B_0}{z^{-n} + B_0^n} \\ E_i &= \delta \cdot E_{i-1} \cdot (1 - E_{i-1}) \\ 0 \leq E_0 \leq 1 \quad i &= 1, 2, 3, \dots, N, \delta = 4 \\ E_i^0 &= lb + (ub - lb) \cdot P ; P \in [0,1] \end{aligned} \quad (25)$$

Cryptoprocta search assimilated with Okapi optimization to expand the search ability. The Okapi optimization algorithm is based on the natural deeds of the okapi (Simone *et al.*, 2024). Control and general exercise are found in the okapi life cycle. Okapis are principally circadian, and they will be active for a limited period at nightfall. Okapis are essentially self-contained, approaching females okapi for mating during the breeding season. Okapis own overlying home arrays and habitat in their limited territory. Location of the okapi is demarcated as,

$$O_{i,j \in N} = \{O_{ij1}, O_{ij2}, O_{ij3}, \dots, O_{ijn}\} \quad (26)$$

$$\begin{aligned} O_{ij} &= (O_{ub} - O_{lb})A + O_{lb} \\ ub, lb &\rightarrow \text{upper and lower bounds} \\ A &\in [0,1] \end{aligned} \quad (27)$$

Okapi, along with young ones, will feed on the leaves and grasses in the habitat.

$$\overline{O}_i^j = \begin{cases} 2A_1 \sin(2\pi A_2) * (O_s^j - O_i^j) \\ + O_s^j, \text{ if } A_3 < 0.5 \\ 2A_1 \cos(2\pi A_2) * (O_s^j - O_i^j) \\ + O_s^j, \text{ otherwise} \end{cases} \quad (28)$$

$O_s^j, O_i^j \rightarrow$  location of the okapi  
 $i \in N_j$

$$O_i^j = \begin{cases} \overline{O}_i^j, \text{ if } \overline{F}_i^j < F_i^j \\ O_i^j, \text{ otherwise} \end{cases}$$

$$A_1 \in [-2, 2], A_2 = 1 - t \cdot \left(\frac{1}{T}\right), A_3 \in [0, 1]$$

During the breeding season, male okapi mate with the female and offspring are engendered.

$$O_j^H = C(O_i^r - O_j^s) \text{ if } a < Z \quad (29)$$

$$O_k^H = C(O_i^r - O_j^s) \text{ if } a \geq Z \quad (30)$$

$C \rightarrow$  crossover

$i, j, k \in N$

$O_j^H, O_k^H \rightarrow$  location of the okapi

$O_i^r, O_j^s \rightarrow$  offsprings

The male okapi guides the family in the migration to find the water and grasslands.

$$\overline{O}_p^j = \begin{cases} 2A_4 \sin(2\pi A_5) * (Q - O_p^j) \\ + Q, \text{ if } A_6 < 0.5 \\ 2A_4 \cos(2\pi A_5) * (Q - O_p^j) \\ + Q, \text{ otherwise} \end{cases} \quad (31)$$

$$O_p^j = \begin{cases} \overline{O}_p^j, \text{ if } \overline{F}_p^j < F_p^j \\ O_p^j, \text{ otherwise} \end{cases}$$

$\overline{O}_p^j \rightarrow$  male okapi guide the movement

$$A_4 \in [-2, 2], A_5 = 1 - t \cdot \left(\frac{1}{T}\right), A_6 \in [0, 1]$$

### Advanced Osteolaemus search optimization (AOSO) algorithm

- Begin
- Arbitrarily generate the positions
- Streamline decreasing parameter
- $E(t) = 2.0 * R_3 * \left(1 - \frac{1}{T}\right)$
- Modernize the stalking operator
- $\varphi_{(i,j)}(t) = L_j(t) * U_{(i,j)}$
- $O_{(i,j)}(t) = \frac{L_j(t) - O_{(R_2,j)}}{L_j(t) + \varepsilon}$
- obtain difference between best and current position
- $U_{(i,j)} = \beta + \frac{\varphi_{(i,j)} - A(O_i)}{L_j(t) * (\max_j - \min_j) + \varepsilon}$
- if  $t \leq T/4.0$ , then tall marching
- $o_{i,j}(t+1) = L_j(t) \cdot -\varphi_{(i,j)}(t) \cdot \alpha - O_{(i,j)}(t) * r$

- Else if  $t \leq 2.T/4.0$  and  $t > T/4.0$ , then tummy marching
- $o_{i,j}(t+1) = L_j(t) \cdot o_{(R_1,j)} \cdot E(t) * \text{random}$
- Else if  $t \leq 3.0.T/4.0$  and  $t > 2.0.T/4.0$ , then stalking synchronization
- $o_{i,j}(t+1) = L_j(t) * U_{(i,j)} * \text{random}$
- Else if  $t \leq T$  and  $t > 3.0.T/4.0$ , then stalking collaboration
- $o_{i,j}(t+1) = L_j(t) \cdot -\varphi_{(i,j)}(t) \cdot \varepsilon - O_{(i,j)}(t) * \text{random}$
- Define the location of cryptoprocta
- $E_{i,j}^{L1} = E_{i,j} + P \cdot (X_{i,j} - D_1 \cdot E_{i,j})$
- Identify the new location of cryptoprocta
- $E_{i,j}^{L2} = E_{i,j} + P \cdot (Z_j - D_2 \cdot E_{i,j})$
- Define the feasible conditions of attack
- $E_{i,j}^{L3} = E_{i,j} + (1 - 2 \cdot P) \cdot \frac{ub_j - lb_j}{t}$
- Apply Logistic chaos mapping
- $A_{n+1} = zA_n(1 - A_n)$
- Define the okapis location
- $\overline{O}_i^j = \begin{cases} 2A_1 \sin(2\pi A_2) * (O_s^j - O_i^j) \\ + O_s^j, \text{ if } A_3 < 0.5 \\ 2A_1 \cos(2\pi A_2) * (O_s^j - O_i^j) \\ + O_s^j, \text{ otherwise} \end{cases}$
- $O_j^H = C(O_i^r - O_j^s) \text{ if } a < Z$
- $O_k^H = C(O_i^r - O_j^s) \text{ if } a \geq Z$
- $\overline{O}_p^j = \begin{cases} 2A_4 \sin(2\pi A_5) * (Q - O_p^j) \\ + Q, \text{ if } A_6 < 0.5 \\ 2A_4 \cos(2\pi A_5) * (Q - O_p^j) \\ + Q, \text{ otherwise} \end{cases}$
- End

## Results and Discussion

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are validated in 7 benchmark functions (Yapıcı and Çetinkaya, 2017). Outcomes are displayed in Table 1.

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

$$f_7(\text{Goldstein} - \text{Price}) = \{1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)\} \times \left\{ \begin{array}{l} 30 + (2x_1 - 3x_2)^2 \\ 18 - 32x_1 + \\ 12x_1^2 + 48x_2 - \\ 36x_1x_2 + 27x_2^2 \end{array} \right\}$$

**Table 1. Result of eepo and aoso in 7 benchmark functions**

| Function | HDPSO<br>(Yapıcı and<br>Çetinkaya,<br>2017) | ANPSO<br>(Yapıcı and<br>Çetinkaya,<br>2017) | EEPO     | AOSO     |
|----------|---------------------------------------------|---------------------------------------------|----------|----------|
| F1       | 0.8874                                      | 0.0026                                      | 0.0035   | 0.0035   |
| F2       | 0.0918                                      | 0.0125                                      | 0.0139   | 0.0139   |
| F3       | 22.9814                                     | 16.5622                                     | 16.532   | 16.532   |
| F4       | 1.1092 e-2                                  | 3.459 e-4                                   | 3.59 e-4 | 3.59 e-4 |
| F5       | -3.8629                                     | -3.8629                                     | -3.8629  | -3.8629  |
| F6       | -1.0318                                     | -1.0316                                     | -1.0317  | -1.0317  |
| F7       | 3.0280                                      | 3.0130                                      | 3.0171   | 3.0171   |

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are applied for solving the true power loss reduction problem, and the objective function is scientifically delineated as,

$$\begin{aligned} & \text{Min } \tilde{F}(\bar{a}, \bar{b}) \\ & a = \left[ \begin{array}{l} VLG_1, \dots, VLG_{Ng}; \\ QC_1, \dots, QC_{Nc}; T_1, \dots, T_{N_T} \end{array} \right] \\ & b = \left[ \begin{array}{l} PG_{slack}; VL_1, \dots, VL_{N_{Load}}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{N_T} \end{array} \right] \\ & F_1 = P_{Min} = \text{Min} \left[ \begin{array}{l} \sum_m^{NTL} G_m \\ [V_i^2 + V_j^2 - 2 * V_i V_j \cos \theta_{ij}] \end{array} \right] \\ & F_2 = \text{Min} \left[ \begin{array}{l} \sum_{i=1}^{N_{LL}} |V_{Lk} - V_{Lk}^{desired}|^2 \\ + \sum_{i=1}^{Ng} |Q_{GK} - Q_{KG}^{lim}|^2 \end{array} \right] \\ & F_3 = \text{Minimize } L_{Maximum} \\ & F = F_1 + r_1 F_2 + u F_3 = F_1 + \left[ \sum_{i=1}^{NL} x_v [VL_i - VL_i^{min}]^2 + \sum_{i=1}^{NG} r_g [QG_i - QG_i^{min}]^2 \right] + r_f F_3 \end{aligned}$$

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are validated in the IEEE 30 bus system. Table 2, display the assessment of results. TES (MW) - true power loss, VDE (PU) - voltage deviation, VSL (PU) - voltage stability. Attained true power loss values are: EEPO - 4.0011 (MW) and AOSO - 4.0009 (MW)

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are validated in the IEEE 57 bus system. Table 3, shows the estimation of results. Attained true power loss values are: EEPO - 20.0512 (MW) and AOSO - 20.0499 (MW)

**Table 2. Estimation Of Results - Ieee 30 Bus System**

| Method                                  | TES<br>(MW) | VDE<br>(PU) | VSL<br>(PU) |
|-----------------------------------------|-------------|-------------|-------------|
| EPU (Pg <i>et al.</i> , 2022)           | 4.6482      | 0.0802      | 0.1004      |
| MCO (Abd-El Wahab <i>et al.</i> , 2022) | 4.9448      | 0.1212      | 0.1232      |
| EOI (Habib Khan <i>et al.</i> , 2022)   | 4.5677      | 0.1250      | 0.1135      |
| ATN (Ali <i>et al.</i> , 2023)          | 4.5464      | 1.9889      | 0.1294      |
| GIA (Varan <i>et al.</i> , 2023)        | 4.1781      | 0.4697      | 0.1323      |
| PSP1 (Lian, 2022)                       | 4.6304      | 0.1678      | 0.2524      |
| EEPO                                    | 4.0011      | 0.0151      | 0.4202      |
| AOSO                                    | 4.0009      | 0.0149      | 0.4206      |

**Table 3. assessment of results - ieee 57 bus system**

| Method                              | TES<br>(MW) | VDE<br>(PU) | VSL<br>(PU) |
|-------------------------------------|-------------|-------------|-------------|
| GIA (Varan <i>et al.</i> , 2023)    | 21.9452     | 0.6012      | 0.0948      |
| BRT (Sahli <i>et al.</i> , 2022)    | 23.3235     | 0.5855      | 0.2561      |
| ZPT (Hasanien <i>et al.</i> , 2024) | 25.4715     | 0.6828      | 0.3231      |
| CON (Shaheen <i>et al.</i> , 2023)  | 25.4963     | 0.7990      | 0.3129      |
| EEPO                                | 20.0512     | 0.4273      | 0.4232      |
| AOSO                                | 20.0499     | 0.4270      | 0.4237      |

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are corroborated in the IEEE 118 bus system. Table 4, displays the assessment of outcomes. Attained true power loss values are: EEPO - 121.098 (MW) and AOSO - 121.082 (MW)

**Table 4. Valuation of results -ieee 118 bus system**

| Method                              | TES (MW) | VDE (PU) |
|-------------------------------------|----------|----------|
| GIA (Varan <i>et al.</i> , 2023)    | 128.137  | 1.12945  |
| BRT (Sahli <i>et al.</i> , 2022)    | 123.511  | 1.21790  |
| ZPT (Hasanien <i>et al.</i> , 2024) | 130.324  | 1.26103  |
| CON (Shaheen <i>et al.</i> , 2023)  | 131.845  | 1.26654  |
| EEPO                                | 121.098  | 1.20096  |
| AOSO                                | 121.082  | 1.20088  |

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm are validated Egyptian Grid 220 Kv system (Mouwafi *et al.*, 2022). Table 5, displays the appraisal of results. Attained true power loss values are: EEPO - 27.69 (MW) and AOSO - 27.63 (MW)

**Table 5. Evaluation of outcomes -220kv network**

| Method                                 | TL (MW) | VL (PU) |
|----------------------------------------|---------|---------|
| PPN (Mouwafi <i>et al.</i> , 2022)     | 32.31   | 0.58    |
| TOI (Abou El-Ela <i>et al.</i> , 2019) | 33.87   | 0.63    |
| ITD (Abou El-Ela <i>et al.</i> , 2019) | 30.78   | 0.67    |
| EEPO                                   | 27.69   | 0.50    |
| AOSO                                   | 27.63   | 0.47    |

**Table 6. Eepo and aoso computation time**

| METHOD | 30 BUS<br>T (S) | 57 BUS<br>T (S) | 118 BUS<br>T (S) | 220KV<br>T (S) |
|--------|-----------------|-----------------|------------------|----------------|
| EEPO   | 14.72           | 19.11           | 32.20            | 16.82          |
| AOSO   | 14.70           | 19.07           | 32.18            | 16.79          |

Table 6, show the computation time of the Enhanced Equus Ferus Przewalskii optimization

(EEPO) algorithm and the Advanced Osteolaemus search optimization (AOSO) algorithm.

### Discussion of results

The improved Equus Ferus Przewalskii optimization (EEPO) algorithm and the advanced Osteolaemus search optimization (AOSO) algorithm effectively and competitively reduced power loss. The Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and the advanced Osteolaemus search optimization (AOSO) algorithm were tested on 7 standard functions, as well as the IEEE 30, 57, and 118 bus systems, and the Grid 220 kv system. Comparison with other standard algorithms shows the better performance of the proposed EEPO and AOSO algorithms. Voltage stability is enhanced with the minimization of voltage deviation.

### Conclusions

Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and Advanced Osteolaemus search optimization (AOSO) algorithm solved the problem proficiently. Based on their group association, we can categorise Equus Ferus Przewalskii into two distinct classes. Equus Ferus Przewalskii lives in clusters of dissimilar eternities, such as young, steeds, and mounts. Vibrant inertia weight approach has been used in the procedure, and Steeds discovers a superior oasis. Cluster frontrunners, referred to as steeds, will guide other cluster members to a suitable area (oasis). Cluster frontrunners (steeds) will also contend for the oasis, leading the foremost cluster to engage the oasis first. The Equus Ferus Przewalskii optimization algorithm is combined with the Anarchias seychellensis and Peacock hind's teamwork-based optimization algorithm to improve how well the process can explore. The design of Osteolaemus search optimization incorporates an exploration performance ring action. Osteolaemus have double passages in the course of the ringing; tall marching and tummy marching. These passages refer to dissimilar sways, which guarantee the exploration search, Osteolaemus passages (tall marching and tummy marching) will not allow them to reach their target prey because of the noise they make, unlike another method of stalking. In accumulation, the exploration modes functioned at this phase of optimization to sustain the additional segment, stalking in the exploration procedure through widespread and extensive investigation. The osteolaemus search optimization algorithm has assimilated the advanced cryptoprocta search optimization algorithm. This assimilation will

upgrade the exploitation competence of the process substantially. The Enhanced Equus Ferus Przewalskii optimization (EEPO) algorithm and the advanced Osteolaemus search optimization (AOSO) algorithm have been tested successfully on 7 standard functions, as well as the IEEE 30, 57, and 118 bus systems, and the Grid 220 kV system.

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